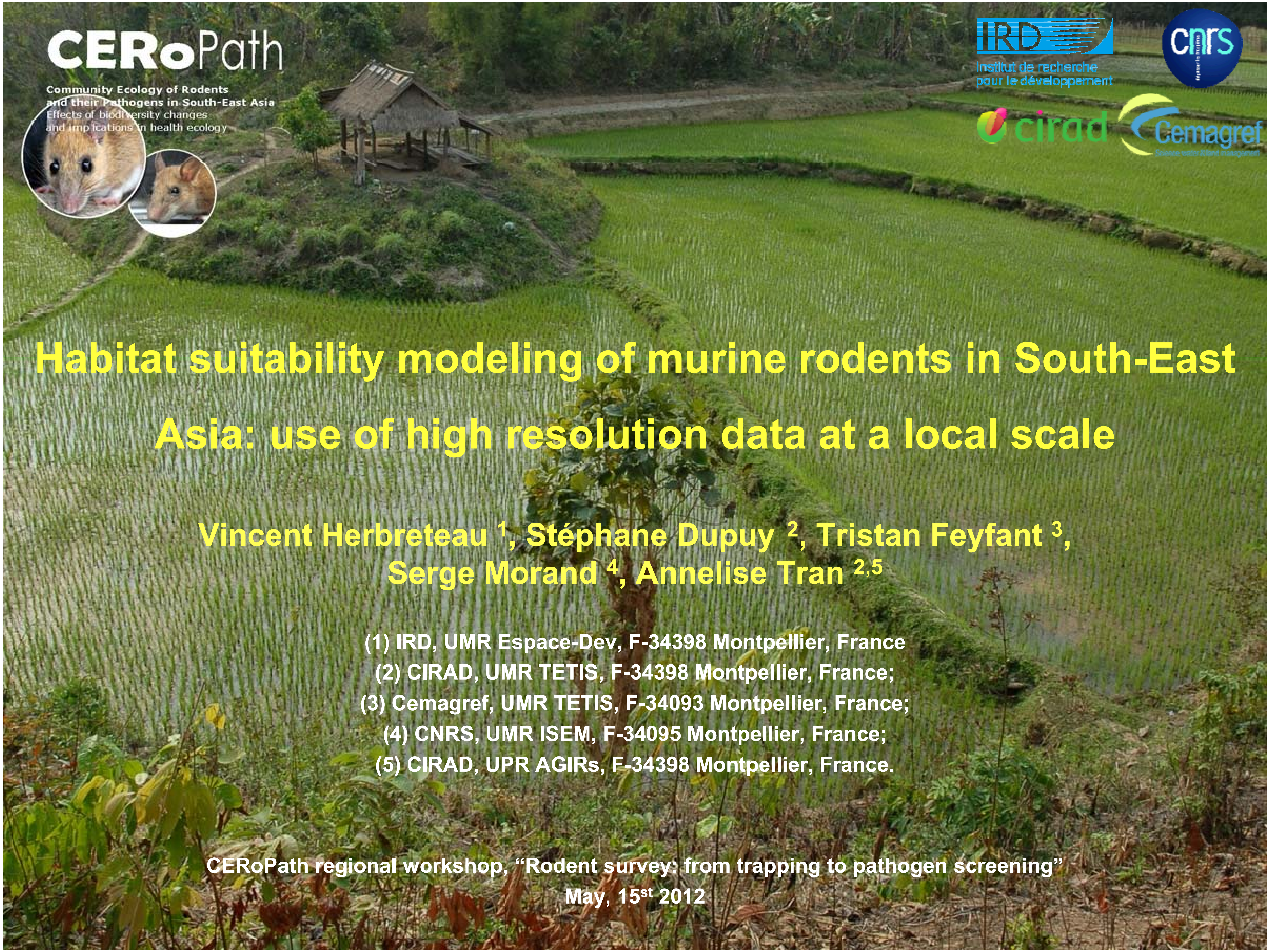

# Habitat suitability modeling of murine rodents in South-East Asia: use of high resolution data at a local scale

Vincent Herbreteau [1], Stéphane Dupuy [2], Tristan Feyfant [3], Serge Morand [4], Annelise Tran [2,5]

(1) IRD, UMR Espace-Dev, F-34398 Montpellier, France
(2) CIRAD, UMR TETIS, F-34398 Montpellier, France;
(3) Cemagref, UMR TETIS, F-34093 Montpellier, France;
(4) CNRS, UMR ISEM, F-34095 Montpellier, France;
(5) CIRAD, UPR AGIRs, F-34398 Montpellier, France.

CERoPath regional workshop, “Rodent survey: from trapping to pathogen screening”
May, 15[st] 2012

# Background


**CERoPath project** (ANR 07 BDIV 012) **:**

**C**ommunity **E**cology of **Ro**dents and their **Path**ogens in South-East Asia

**www.ceropath.org**

→ aiming at understanding the implication of rodents in the transmission of diseases,

→ in a context of rapid environmental changes.

**Photos: Herbreteau V.**

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# Introduction:

## *Objectives*

### Habitat suitability modeling of murine rodents in South-East Asia

- Understand the influence of spatial ecological heterogeneity on rodent communities.

- Estimate the environmental envelopes of these rodent species.

- Calculate environmental indicators of the presence of the different species

## Can we pretend to model an ecological niche?

• Niche (or ecological niche) = a term describing the relational position of a species or population in its ecosystem

→ **We should distinguish between:**

- the **fundamental niche** = the total range of environmental conditions that are suitable for existence without the influence of interspecific competition or predation from other species;
- the **realized niche** = the part of the fundamental niche actually occupied by the species.

→ study of **“suitable habitats”** i.e. the ecological areas where a species can live.

**Different terms used for niche / habitat modeling:**

Ecological
Environmental
**niche** modeling

**Habitat** suitability modeling

**Resource** selection/use modeling

**Climate** suitability modeling
**Climate** response modeling

**Bio-climate** modeling

Species **distribution** modeling

## Methods used in niche / habitat modeling:

- Relate the known occurrences of a given species to the environmental data.


Source: Open Modeller (http://openmodeller.sourceforge.net)

- Applications are usually based on the Grinnell's definition of ecological niches.

## Methods used in niche / habitat modeling:

- Increasing number of algorithms and softwares developed:
  MaxEnt, ENFA, BIOMOD, Openmodeller, ModEco, GARP, BIOMAPPER, CANOCO, WinBUGS, OpenBUGS, DOMAIN, SPECIES, etc.

  together with statistical models: GLM, GAM, discriminant analysis, etc.

- Usually integrating global datasets (rasters, low spatial resolution)

→ Objectives of our study:

- model species accurately identified, described in the field and precisely located,
- integrate high resolution spatial data.

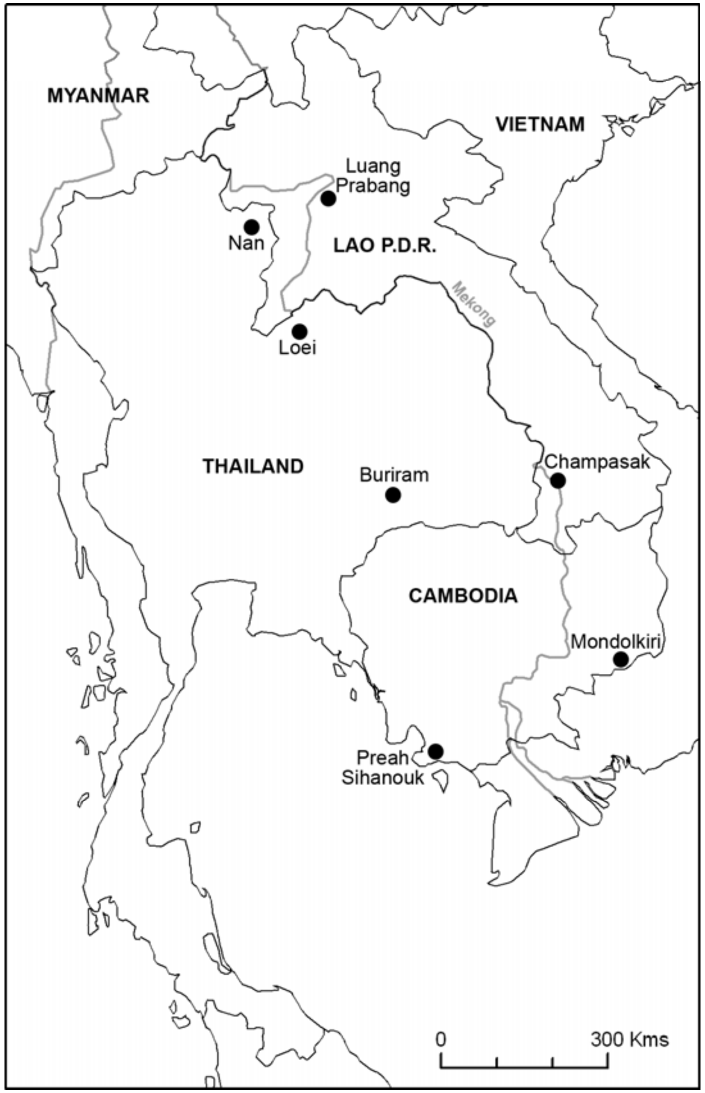
# Material and Methods:

## *Rodent sampling*

### 7 study sites in 3 South-East Asian countries (Cambodia, Lao PDR, Thailand):

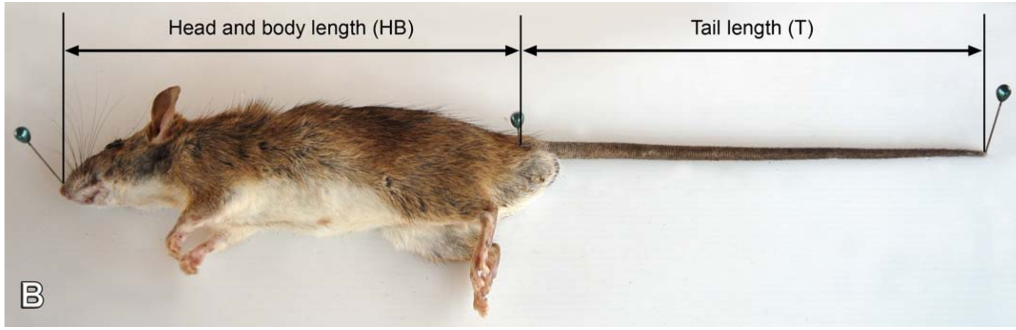
- **Trapping in lines:**
  - 30 lines of 10 traps, left 4 nights:
    - 10 in forested areas,
    - 10 in dry fields,
    - 10 in wet ricefields.
    - → total of 1,200 night-traps
  - trapping during 2 season (wet / dry):
    - → 2,400 night-traps per site
    - → Total of 16,800 night-traps.

- **Complementary trappings:**
  - in villages,
  - in places with signs of rodent  presence,
  - from hunters.



## Rodent identification:

- Use of locally made live-traps.
- Field identification: external measurements and description.
- Genetic identification / CBGP-Montpellier

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# Material and Methods:

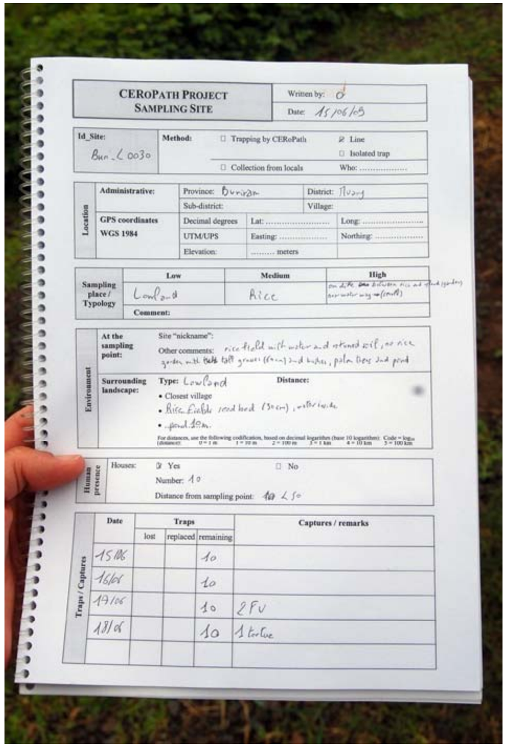
## *Rodent sampling*

### Environmental description:

- GPS locatisation of each sample.

- Description of the surrounding environment: landuse, distance to main landscape features, human presence, etc.

- Pictures taken around the trap:




0°

90°

180°

270°

# Material and Methods:

## *Global data*

- **Climate data:**

  - **Global Precipitation Climatology Centre** (GPCC):

    - Provided by the Deutscher Wetterdienst.

    - Analyses the monthly precipitation on Earth's landsurface based on raingauge station data.

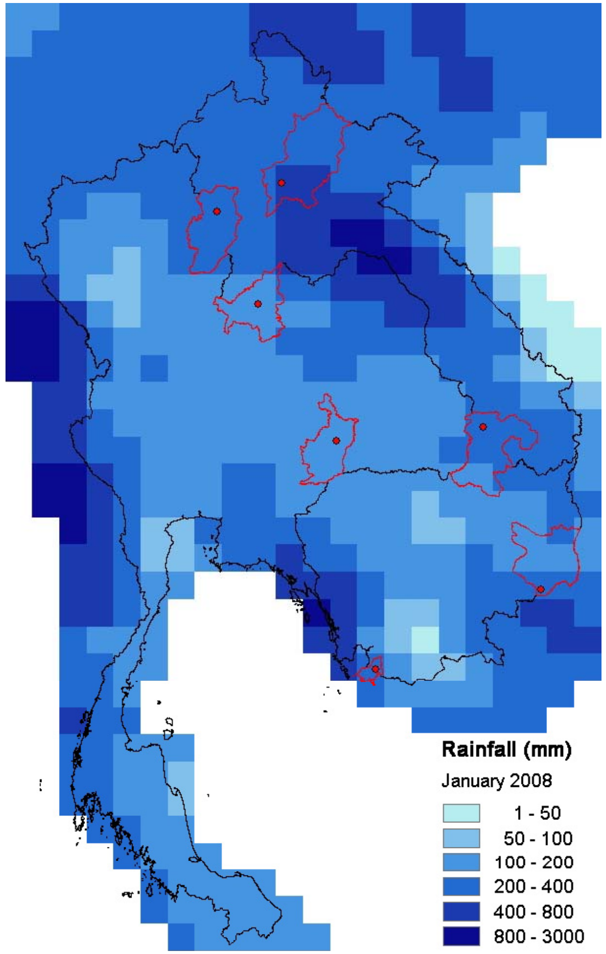
    - 0.5° (55.5 km) spatial resolution.

  - **WorldClim**:

    - compiled from different dataset and provided by: http://www.worldclim.org/.

    - 1/6° (approx. 18.5 km) spatial resolution.

    - 1950-2000 temperature and rainfall data.



# Material and Methods:

## *Global data*

- Climate data:
- **Topographic data:**
  - **Shuttle Radar Topography Mission** (SRTM):

    - Provided by USGS - NASA

    (http://srtm.usgs.gov/)

    - Digital Elevation Model with a 3 arc-second (approx. 90 meters) spatial resolution.

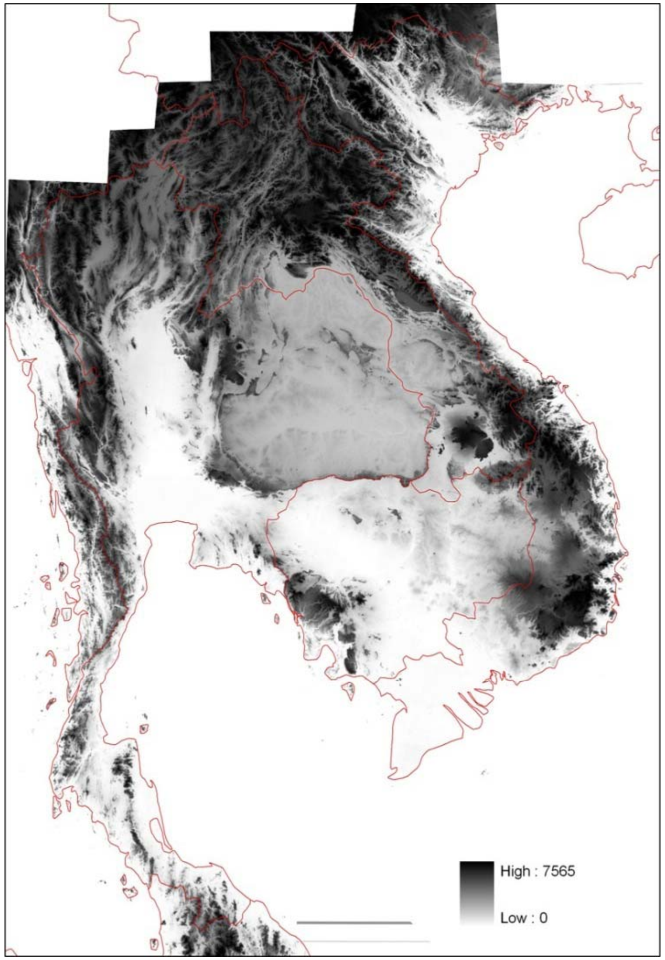
  - **ASTER Global Digital Elevation Model** (GDEM):

    - Provided by USGS - Japan's Ministry of Economy, Trade and Industry

    (http://www.ersdac.or.jp/GDEM/E/)

    - Digital Elevation Model with a 1 arc-second (approx. 30 meters) spatial resolution.

    - Serious artifacts.



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# Material and Methods:

## *Global data*

- Climate data:
- Topographic data:
- **Land cover data**
    - **GlobCover 2.2**:

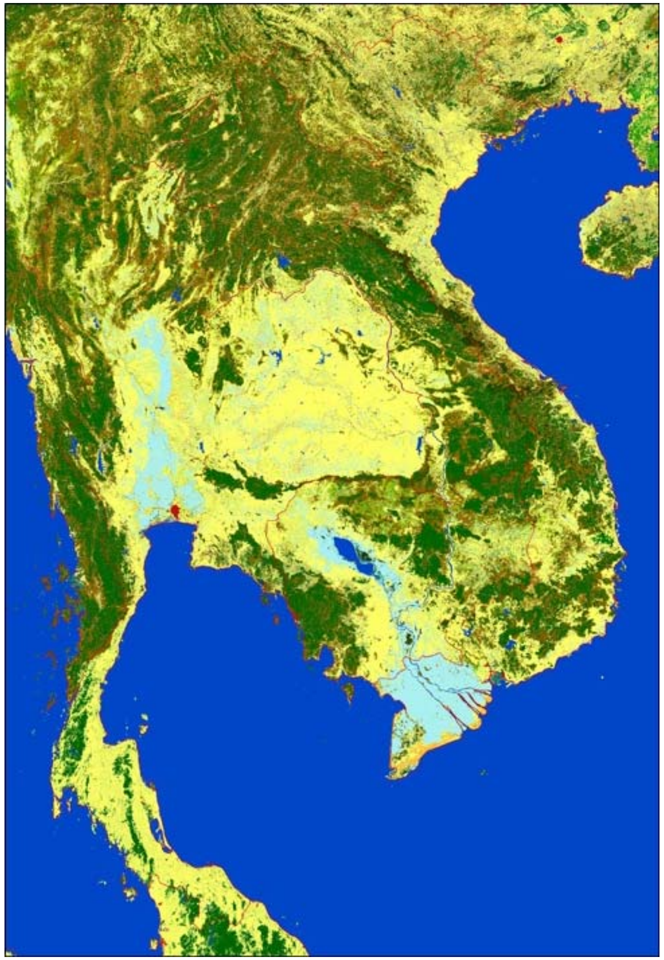
        - Provided by POSTEL (Pôle d'Observation des Surfaces Terrestres aux Echelles Larges) (http://medias.obsmip.fr/postel/)

        - Land cover map (2005-2006) derived from ENVISAT – MERIS satellite images (300 m spatial resolution).

    - **Global Land Cover Facility** (GLCF):

        - Provided by University of Maryland Dpt of Geography (http://www.landcover.org/)

        - Land cover map (1981-1994) derived from AVHRR satellite images (1 km spatial res.).

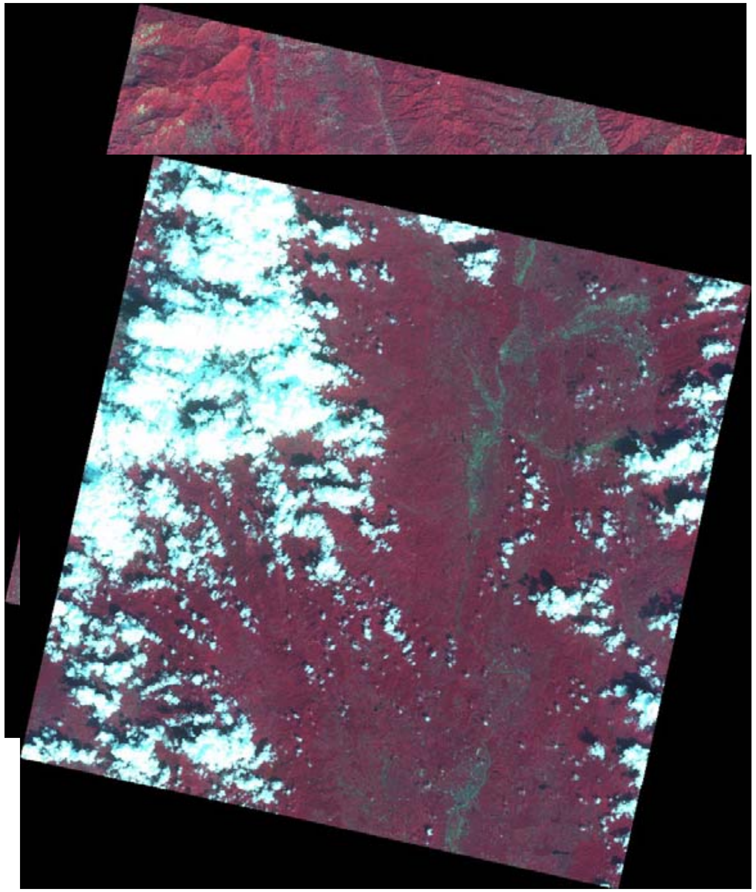


## High resolution information can be gained through remote sensing:

- Acquisition of high resolution SPOT V images.

*SPOT data was provided via the ISIS program operated by the French Space Agency, CNES.*

→ Difficulties to get high quality images from optical sensors in tropical areas



SPOT V image of Nan province, Northern Thailand

# Material and Methods:

## *Local (high resolution) data*

### High resolution information can be gained through remote sensing:

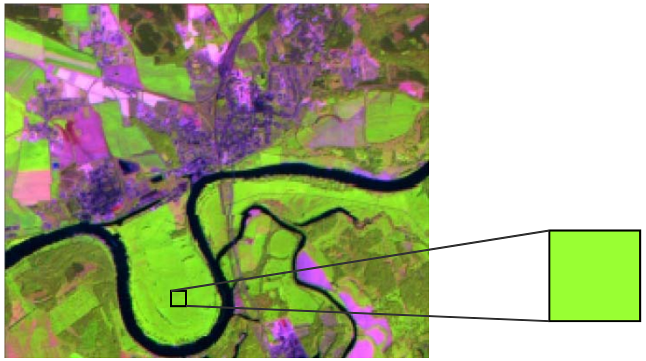
- Acquisition of high resolution SPOT V images.

| Study site | Date | Satellite / sensor | Image type / Spatial resolution |
|---|---|---|---|
| Cambodia - Mondolkiri | 16/03/2008 | SPOT 5 HRG 1 | Pan / 5 . MS / 10 |
| Cambodia - Veal Renh | 19/12/2006 | SPOT 5 HRG 1 | Pan / 2,5 . MS / 10 |
| | 22/03/2007 | SPOT 5 HRG 1 | MS / 10 |
| Lao PDR - Luang Prabang | 31/10/2006 | SPOT 5 HRG 2 | Pan / 2,5 . MS / 10 |
| | 03/01/2007 | SPOT 5 HRG 1 | MS / 10 |
| Lao PDR - Pakse | 13/12/2007 | SPOT 5 HRG 1 | Pan / 2,5 . MS / 10 |
| Thailand - Buriram | 11/11/2006 | SPOT 5 HRG 2 | MS / 10 |
| | 17/01/2008 | SPOT 5 HRG 2 | Pan / 2,5 . MS / 10 |
| Thailand - Loei | 13/01/2007 | SPOT 5 HRG 1 | Pan / 2,5 . MS / 10 |
| | 19/04/2008 | SPOT 5 HRG 2 | MS / 10 |
| Thailand - Nan | 21/10/2006 | SPOT 5 HRG 1 | MS / 10 |
| | 12/01/2007 | SPOT 5 HRG 1 | Pan / 2,5 . MS / 10 |

## Use of Object-Based Image Analysis methods (OBIA):

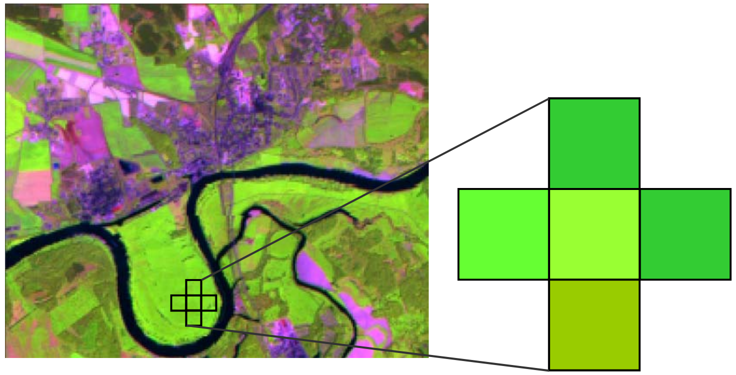
**Different approaches of land-cover classification :**

### Pixel-based classification



**Each pixel is classified according to its spectral signature.**

### Contextual techniques for classification



**Response and class of 2 spatially neighbouring pixels are highly related:**

**pixels are classified according to their context.**

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# Material and Methods:

*Satellite images analysis*

## Different steps:

1. Image pre-processing
2. Image segmentation
3. Image classification
4. Change detection
5. Landscape analysis

# Material and Methods:

## *Satellite images analysis*

### 1- Satellite image pre-processing:

→ with ERDAS Imagine 2010®

- Radiometric calibrations (to make different images comparable):

  1- Conversion of digital numbers (recorded by sensors) to spectral radiance (i.e. total light emitted by the objects), according to the gain and bias of the sensor.

  2- Conversion of spectral radiance to exoatmospheric reflectance (because spectral radiance depends on the degree of illumination of the object, that varies with time of day, season, latitude).

- Resampling the 10 m Multispectral images to 2.5 m resolution of the Panchromatic images.

# Material and Methods:

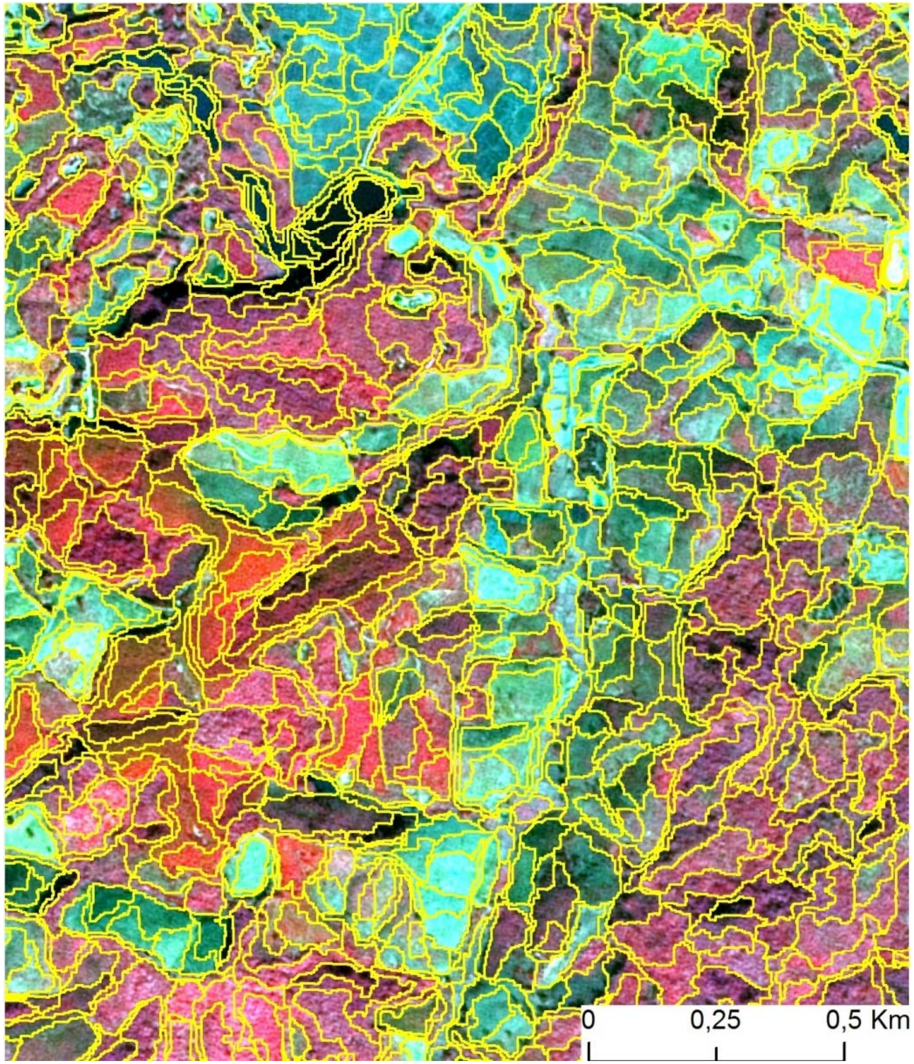
## *Satellite images analysis*

### 2- Image segmentation

(subdivision into homogeneous regions)

→ with eCognition Developer 8®

- Use of a "Multiresolution segmentation" algorithm.
- Applied on the most recent scene.
- Same segmentation parameters for all sites (scale factor, shape and compactness values).
- Two levels of segmentation.




*Segmentation of SPOT image from Loei province, Thailand*

# Material and Methods:

## *Satellite images analysis*

### 3- Image classification

**Preliminary calculations:**

• **Texture indices:** contrast and dissimilarity indices derived from Panchromatic images.

• **Topographic index:** slope derived from DEMs.


*SPOT image from Loei province, Thailand*

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# Material and Methods:

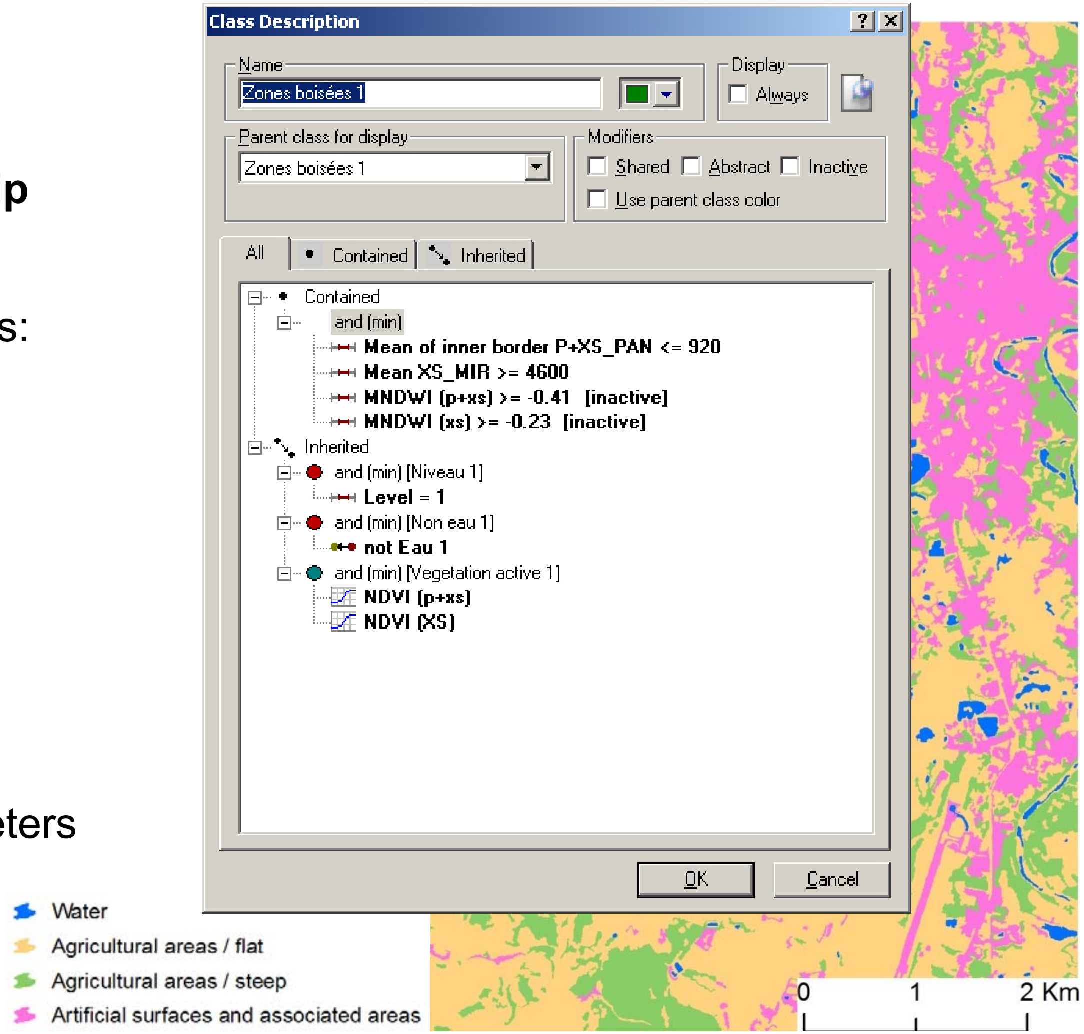
*Satellite images analysis*

## 3- Image classification

**Classification using membership functions:**

- Objects intrinsic characteristics:
  - Reflectance values
  - Shape
  - Texture indices
  - Vegetation indices
  - Water indices
  - Slope

- Same characteristics and membership functions parameters for all sites



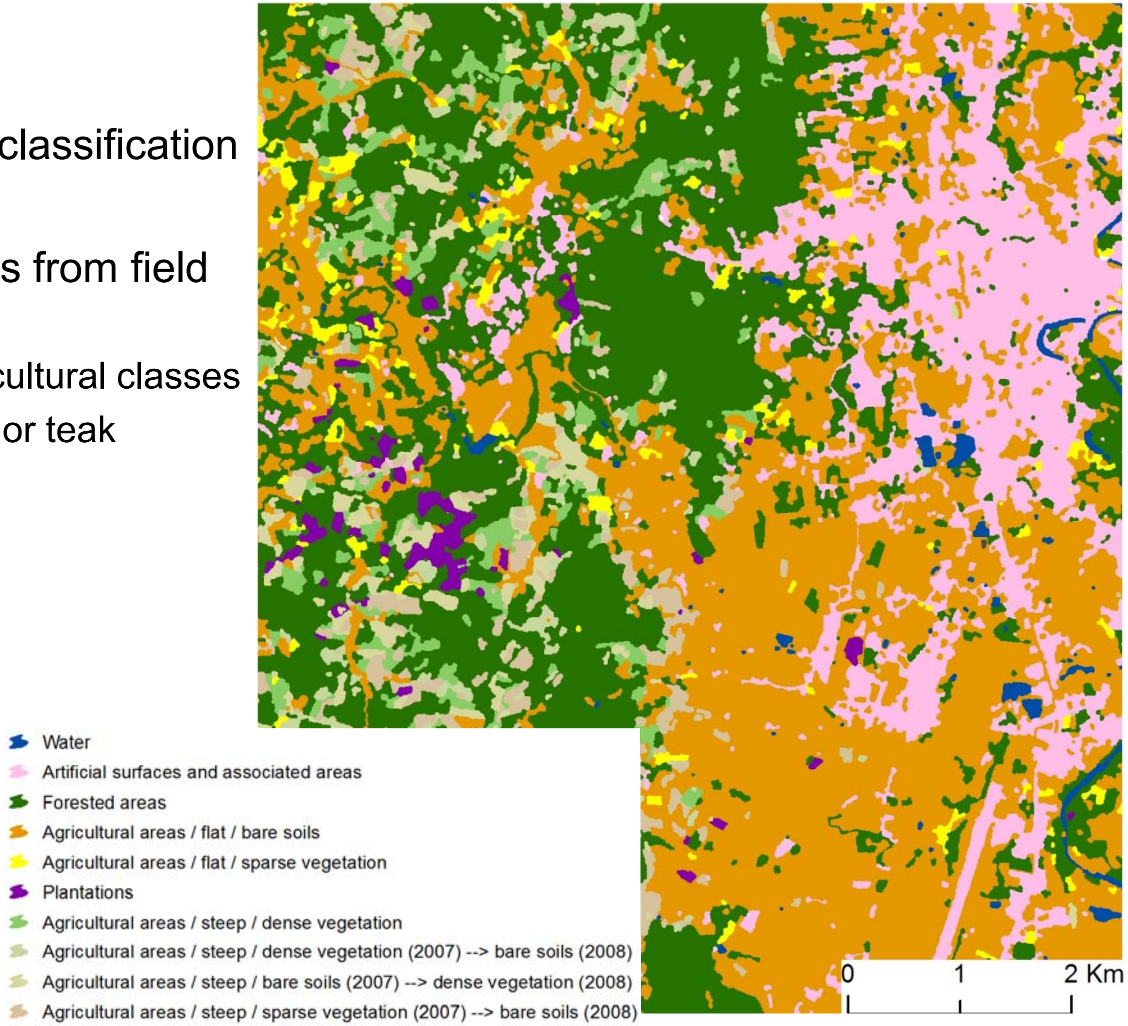

*Level 1 - Classification of SPOT image from Loei province, Thailand*

### 3- Image classification

Supervised nearest neighbour classification

- Selection of training samples from field observations:
  - Different wooded and agricultural classes
  - *e.g.* rice fields, rubber tree or teak plantations

- Site-dependent process


*Level 2 - Classification of SPOT image from Loei province, Thailand*

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# Material and Methods:

*Satellite images analysis*

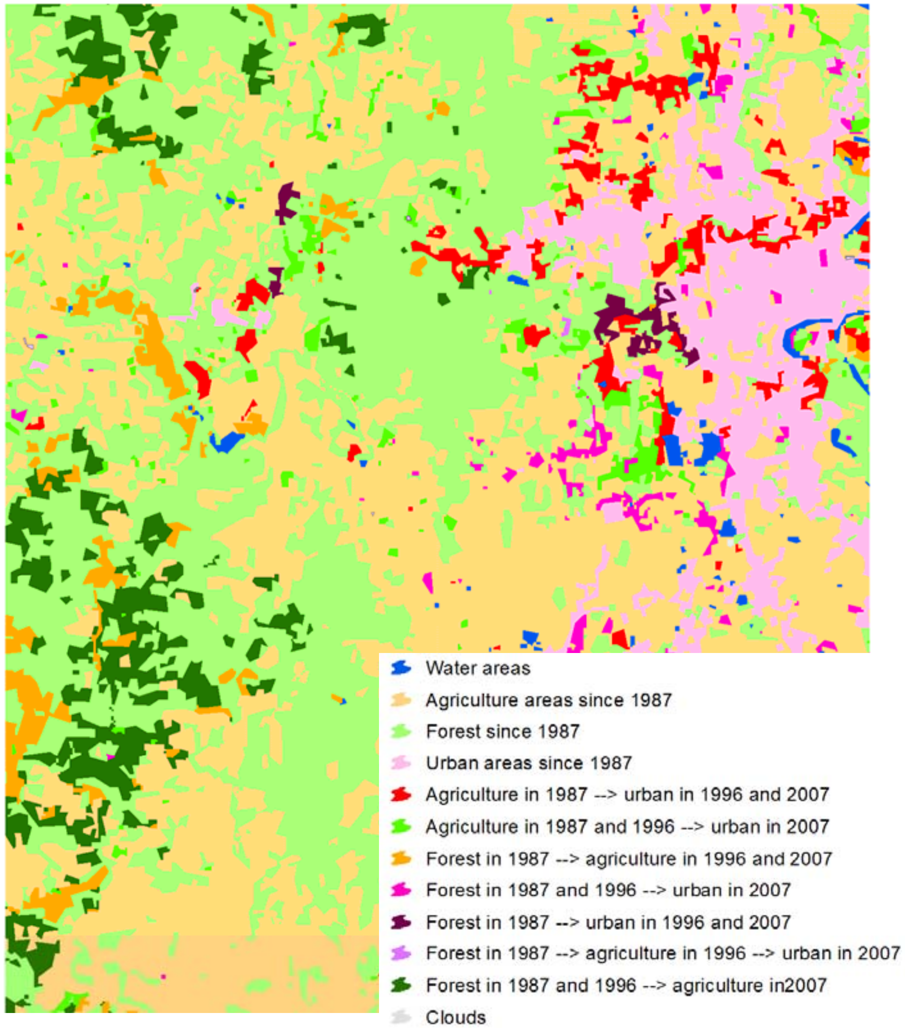
## 4- Change detection

**Object-based classification of older scenes:**

- Merging objects to allow inter-site comparison:
  - Water
  - Wooded areas
  - Cultivated areas
  - Built-up areas

- Segmentation:
  - Based on the 4 classes limits.

- Classification:
  - Intrinsic properties.
  - Topologic characteristics (relations to neighboring objects).
  - Contextual characteristics (semantic relationships).



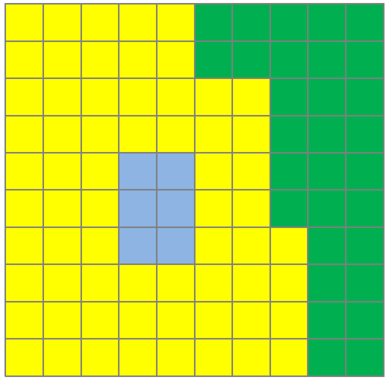

*Land-cover changes, Loei province, Thailand*

# Material and Methods:

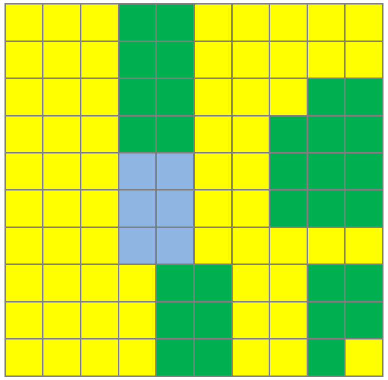
## *Landscape analysis*

**Increasing fragmentation**

Continuous landscape



Fragmented landscape



| Occupation | Area (ha) |
|---|---|
| Forested area | 30 |
| Agricultural area | 64 |
| Water body | 6 |

| | Continuous landscape | Fragmented landscape |
|---|---|---|
| Patch density (patches / ha) | 0.03 | 0.08 |
| Edge density (m / ha) | 0.76 | 1.24 |

$$\text{Patch density} = \frac{\text{Number of patches}}{\text{Total area (ha)}}$$

$$\text{Edge density} = \frac{\text{Total edge (m)}}{\text{Total area (ha)}}$$

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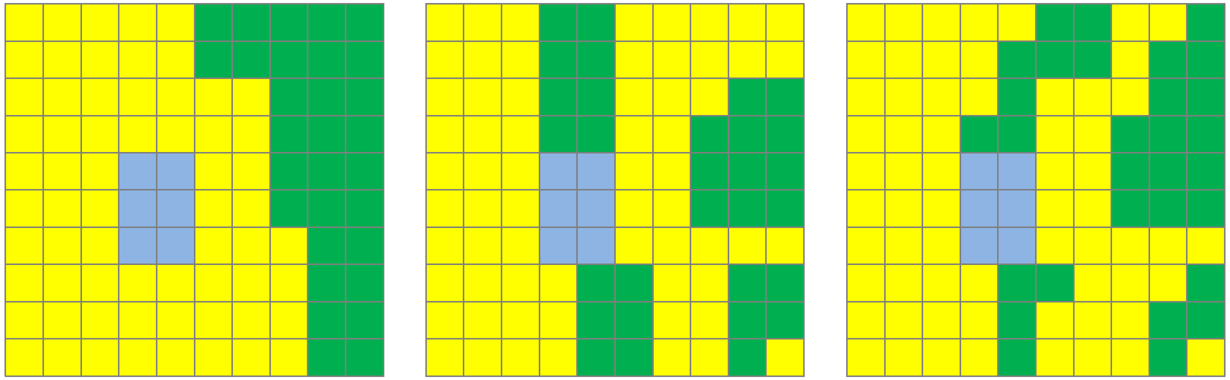
# Material and Methods:

## *Landscape analysis*

**Increasing fragmentation**

| Occupation | Area (ha) |
|---|---|
| Forested area | 30 |
| Agricultural area | 64 |
| Water body | 6 |

Continuous landscape Fragmented landscape



| | | | |
|---|---|---|---|
| Patch density (patches / ha) | 0.03 | 0.08 | 0.08 |
| Edge density (m / ha) | 0.76 | 1.24 | 1.35 |

$$\text{Patch density} = \frac{\text{Number of patches}}{\text{Total area (ha)}} \qquad \text{Edge density} = \frac{\text{Total edge (m)}}{\text{Total area (ha)}}$$

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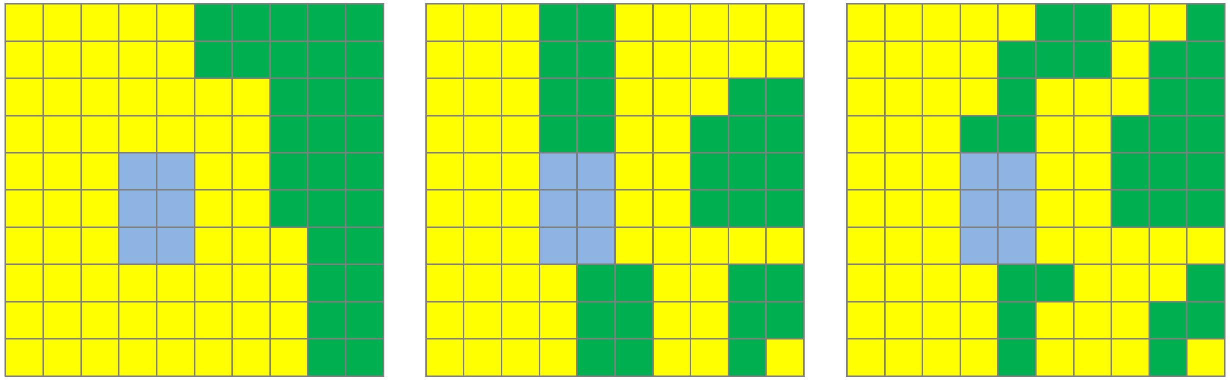
# Material and Methods:

## *Landscape analysis*

**Increasing fragmentation**

Continuous landscape | Fragmented landscape



| Occupation | Area (ha) |
|---|---|
| Forested area | 30 |
| Agricultural area | 64 |
| Water body | 6 |

| | | | |
|---|---|---|---|
| Patch density (patches / ha) | 0.03 | 0.08 | 0.08 |
| Edge density (m / ha) | 0.76 | 1.24 | 1.35 |
| Shannon Diversity Index | 0.82 | 0.82 | 0.82 |

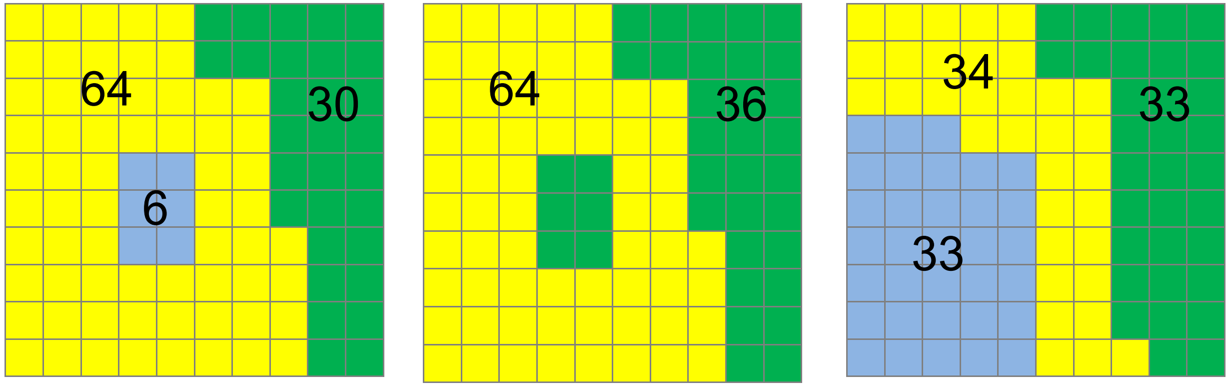
$$\mathrm{SHDI} = -\sum_{i=1}^{m} (Pi * \ln Pi)$$

With $P_i$ = proportion of area covered by land cover class I
wnd : m = number of patch types

# Material and Methods:

## *Landscape analysis*






| | | | |
|---|---|---|---|
| Patch density (patches / ha) | 0.03 | 0.03 | 0.03 |
| Edge density (m / ha) | 0.76 | 0.76 | 0.90 |
| Shannon Diversity Index | 0.82 | 0.65 | 1.10 |

$$SHDI = -\sum_{i=1}^{m}(Pi * \ln Pi)$$

with: $P_i$ = proportion of area covered by land cover class i
and: m = number of patch types

→ SHDI increases:
- with the number of classes,
- as the proportion of each class becomes equal.

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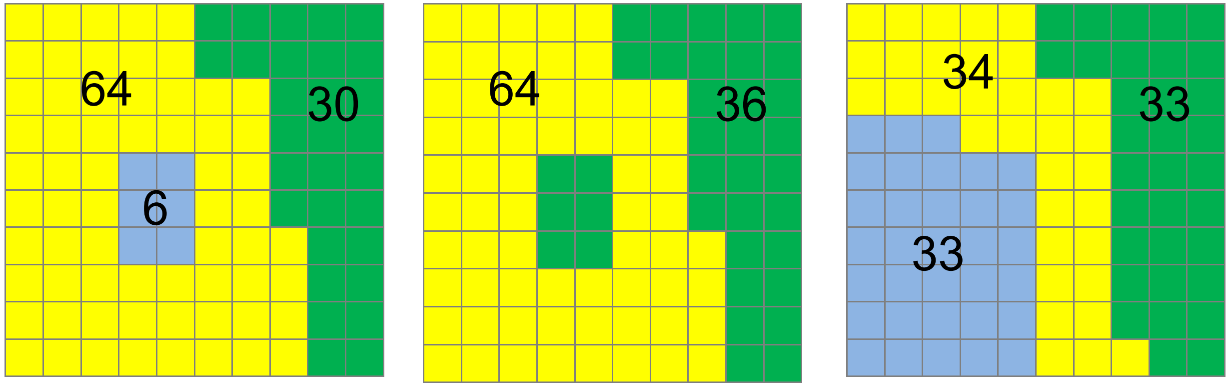
# Material and Methods:

## *Landscape analysis*



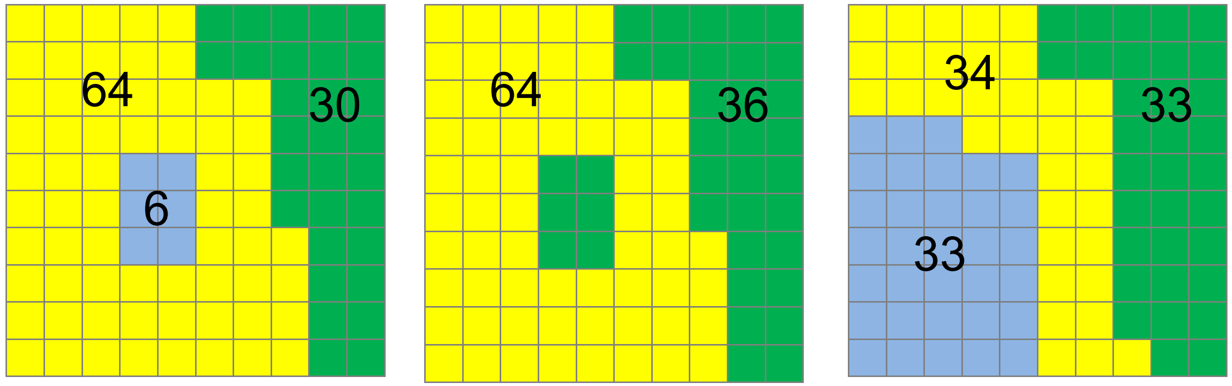

| | | | |
|---|---|---|---|
| Patch density (patches / ha) | 0.03 | 0.03 | 0.03 |
| Edge density (m / ha) | 0.76 | 0.76 | 0.90 |
| Shannon Diversity Index | 0.82 | 0.65 | 1.10 |
| Shannon Evenness Index | 0.74 | 0.94 | 1.00 |

$$SHEI = \frac{SHDI}{\ln m} = \frac{-\sum_{i=1}^{m}(Pi * \ln Pi)}{\ln m}$$

$0 \leq SHEI \leq 1$

# Material and Methods:

## *Landscape analysis*




| | | | |
|---|---|---|---|
| Patch density (patches / ha) | 0.03 | 0.02 | 0.03 |
| Edge density (m / ha) | 0.76 | 0.76 | 0.90 |
| Shannon Diversity Index | 0.82 | 0.65 | 1.10 |
| Shannon Evenness Index | 0.74 | 0.94 | 1.00 |
| Simpson Diversity Index | 0.50 | 0.46 | 0.67 |

$$SIDI = 1 - \sum_{i=1}^{m} Pi^2$$

$$0 \leq SHEI \leq 1$$

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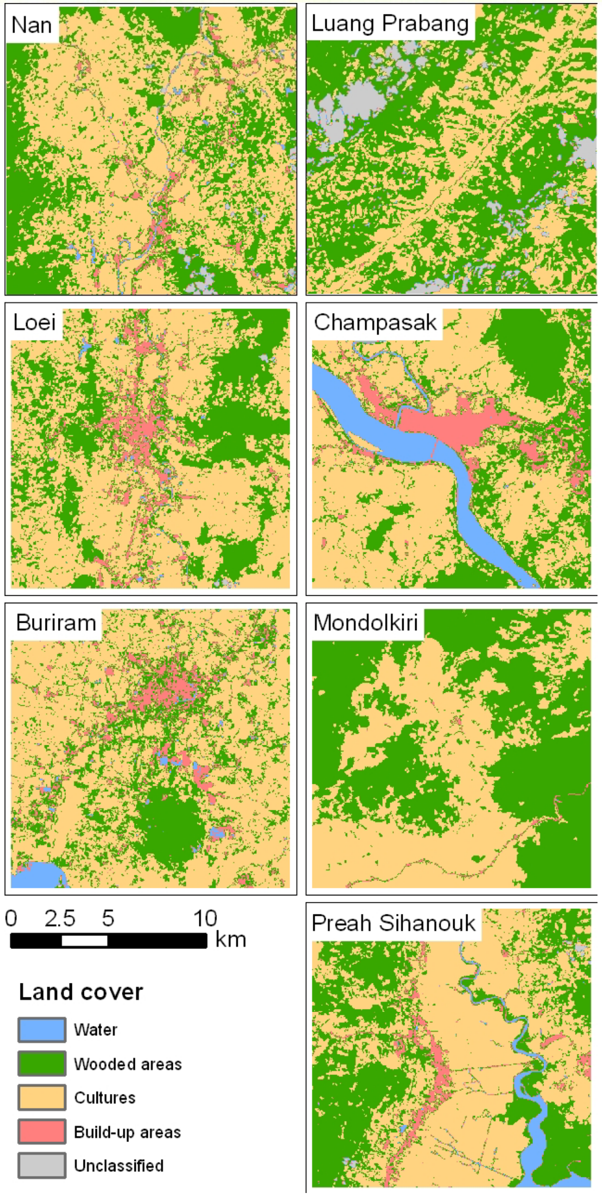
# Results:

## *Land-cover maps*

### Various landscapes

Photos: Morand S.

- 2 sites largely covered by wooded areas (Luang Prabang, Lao PDR, and Mondolkiri, Cambodia)
- 1 site with limited forested areas (Buriram, Thailand)
- Differences in size of forested patches

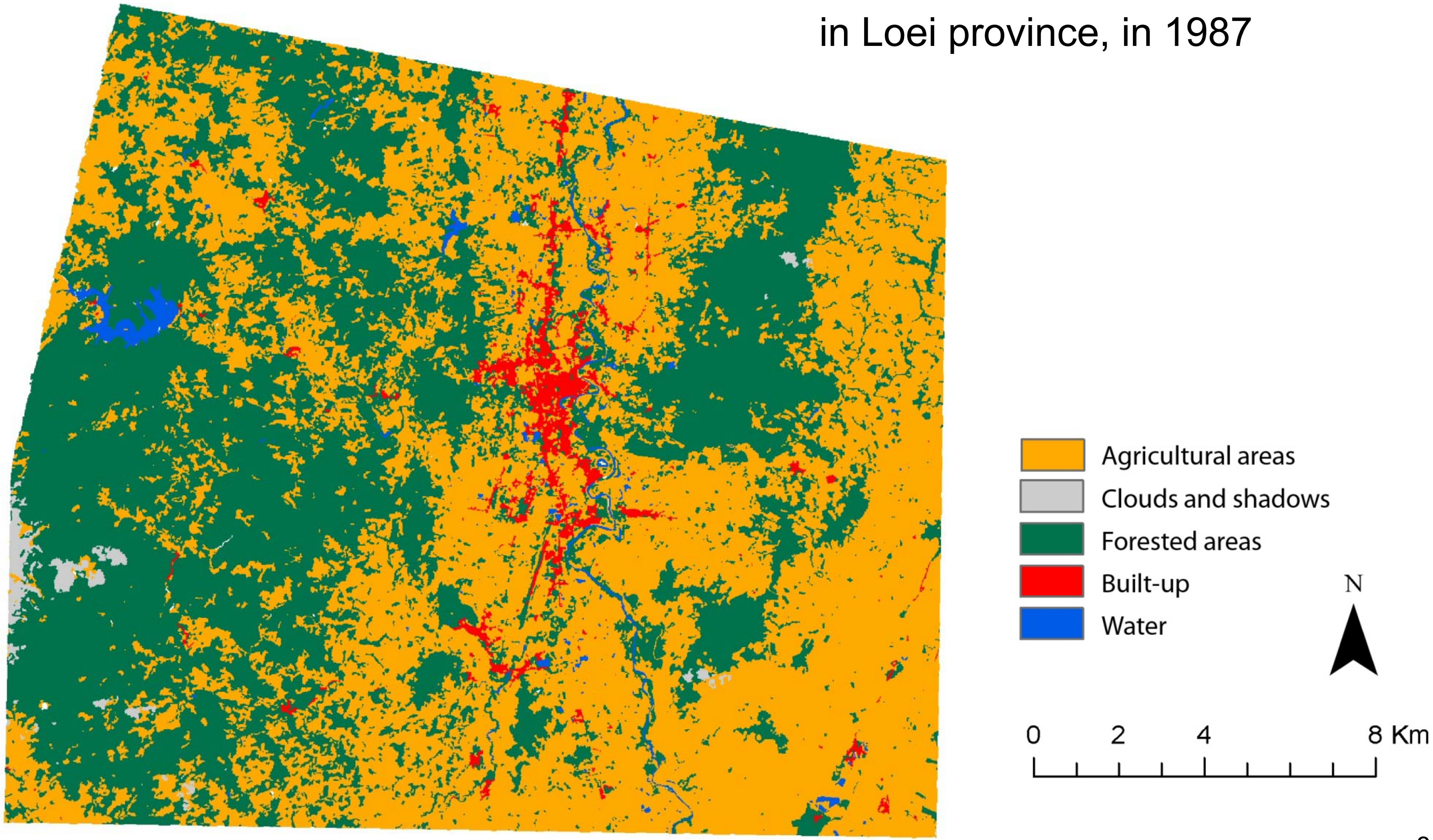


# Results:

## *Land use / cover changes*

Land use / land cover classification

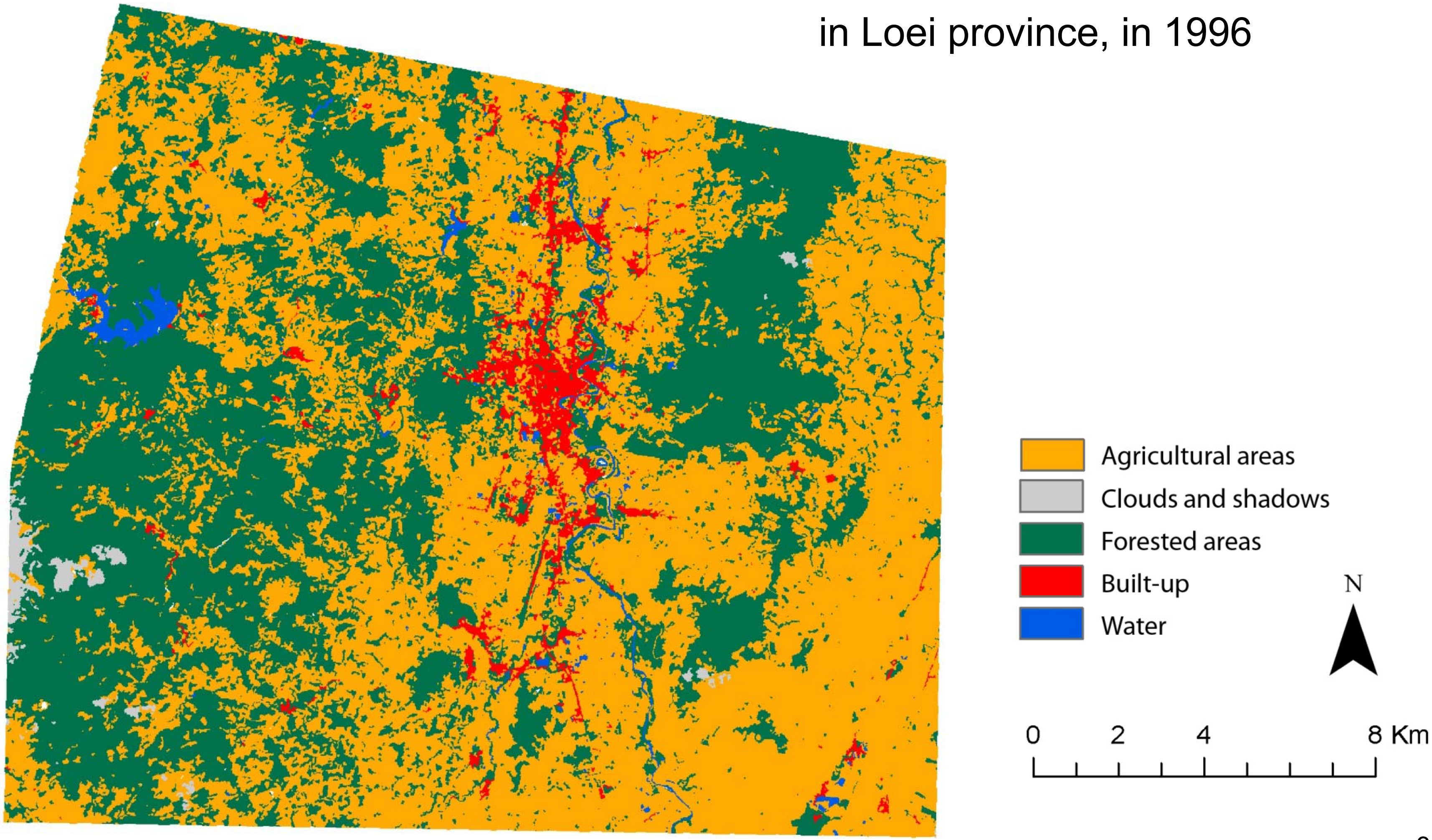
in Loei province, in 1987



# Results:

## *Land use / cover changes*

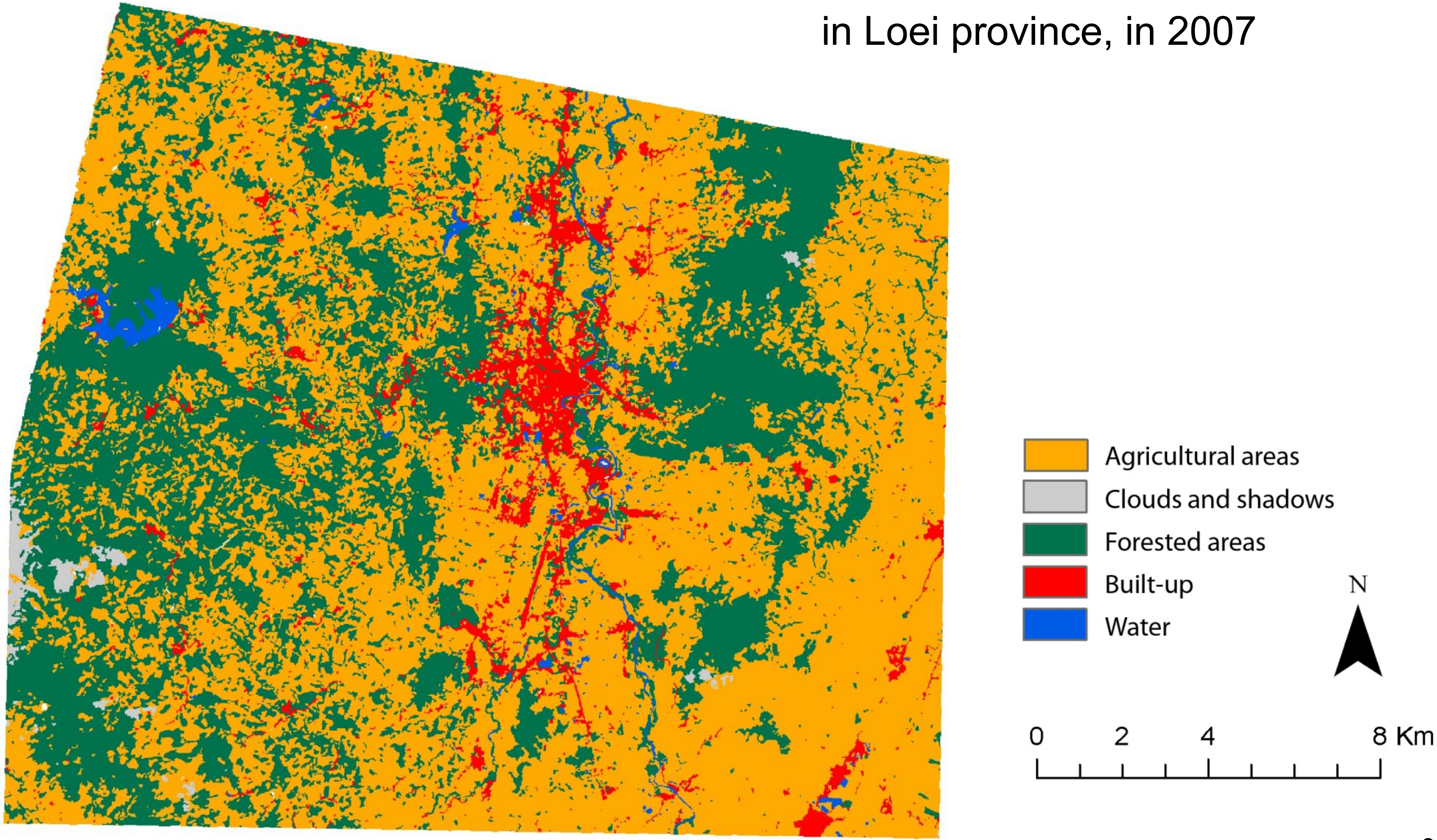
Land use / land cover classification
in Loei province, in 1996



# Results:

## *Land use / cover changes*

Land use / land cover classification
in Loei province, in 2007



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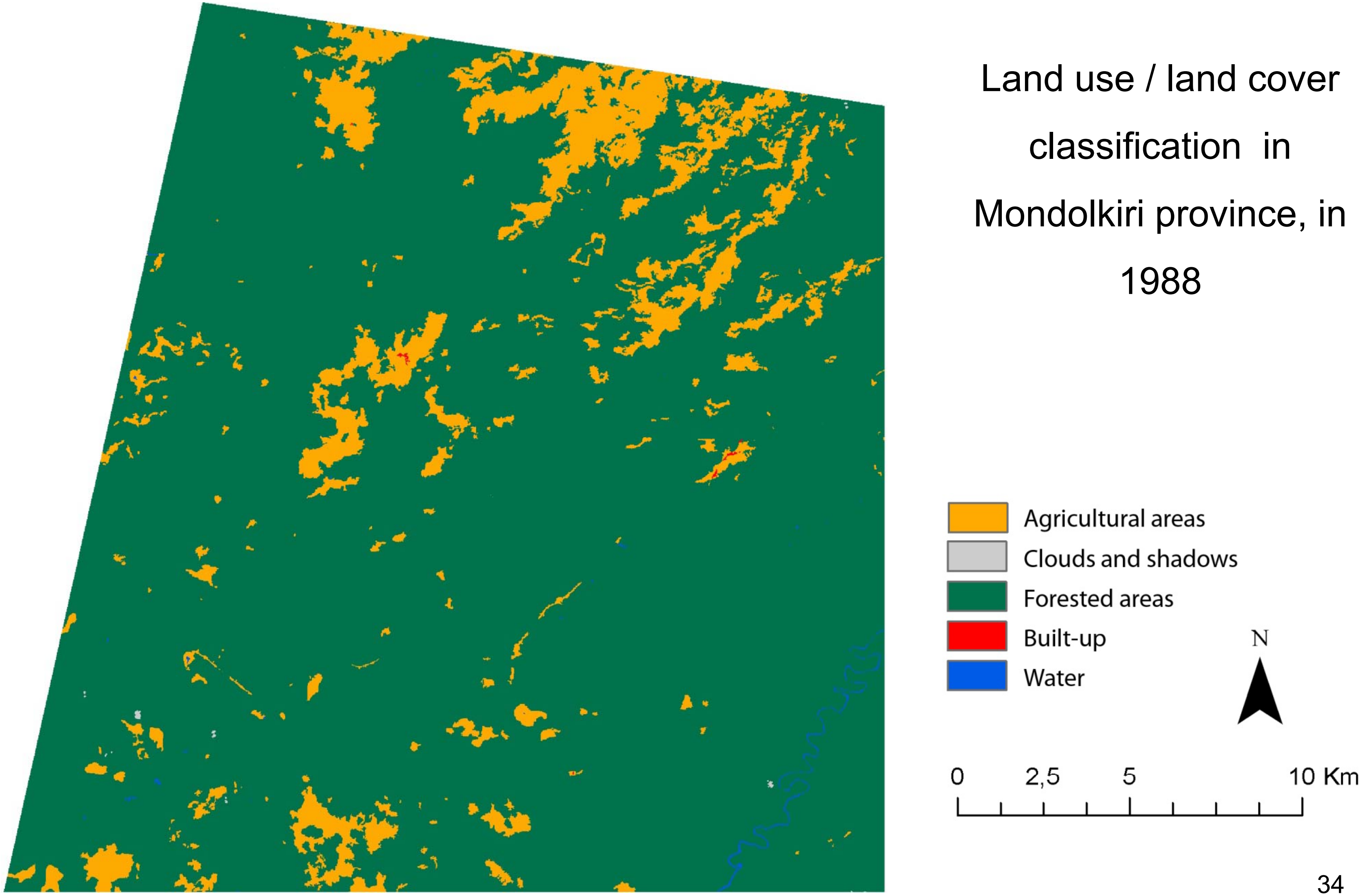
# Results:

## *Land use / cover changes*




Land use / land cover classification in Mondolkiri province, in 1988

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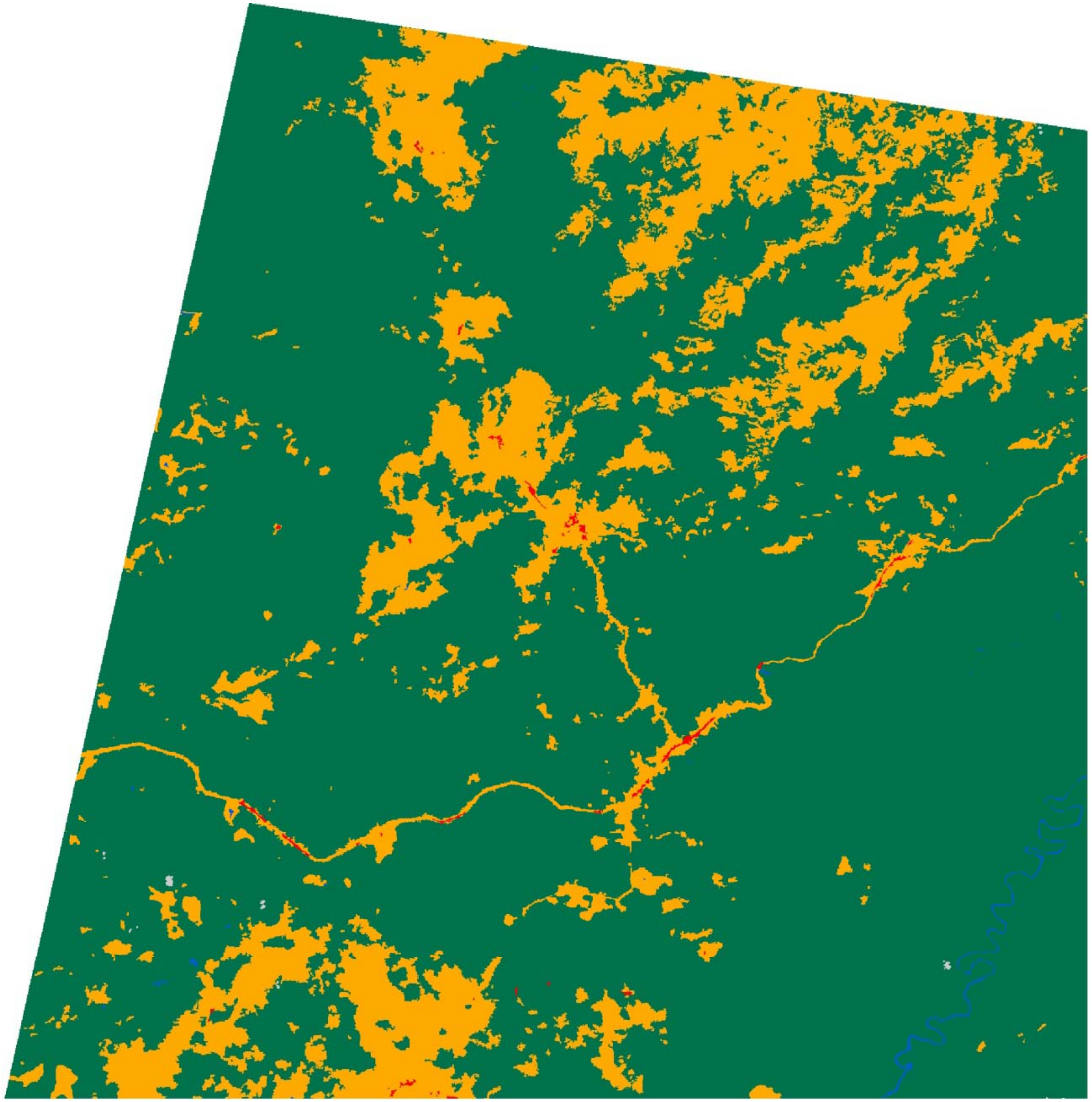
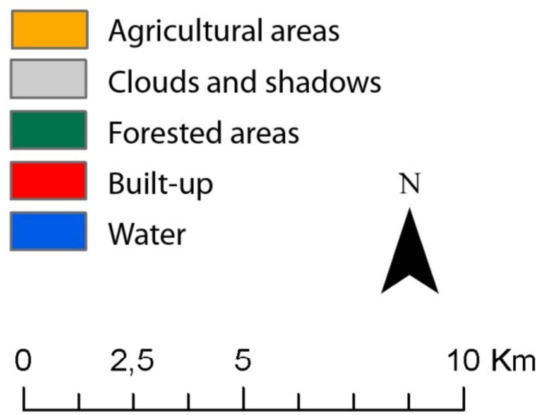
# Results:

## *Land use / cover changes*

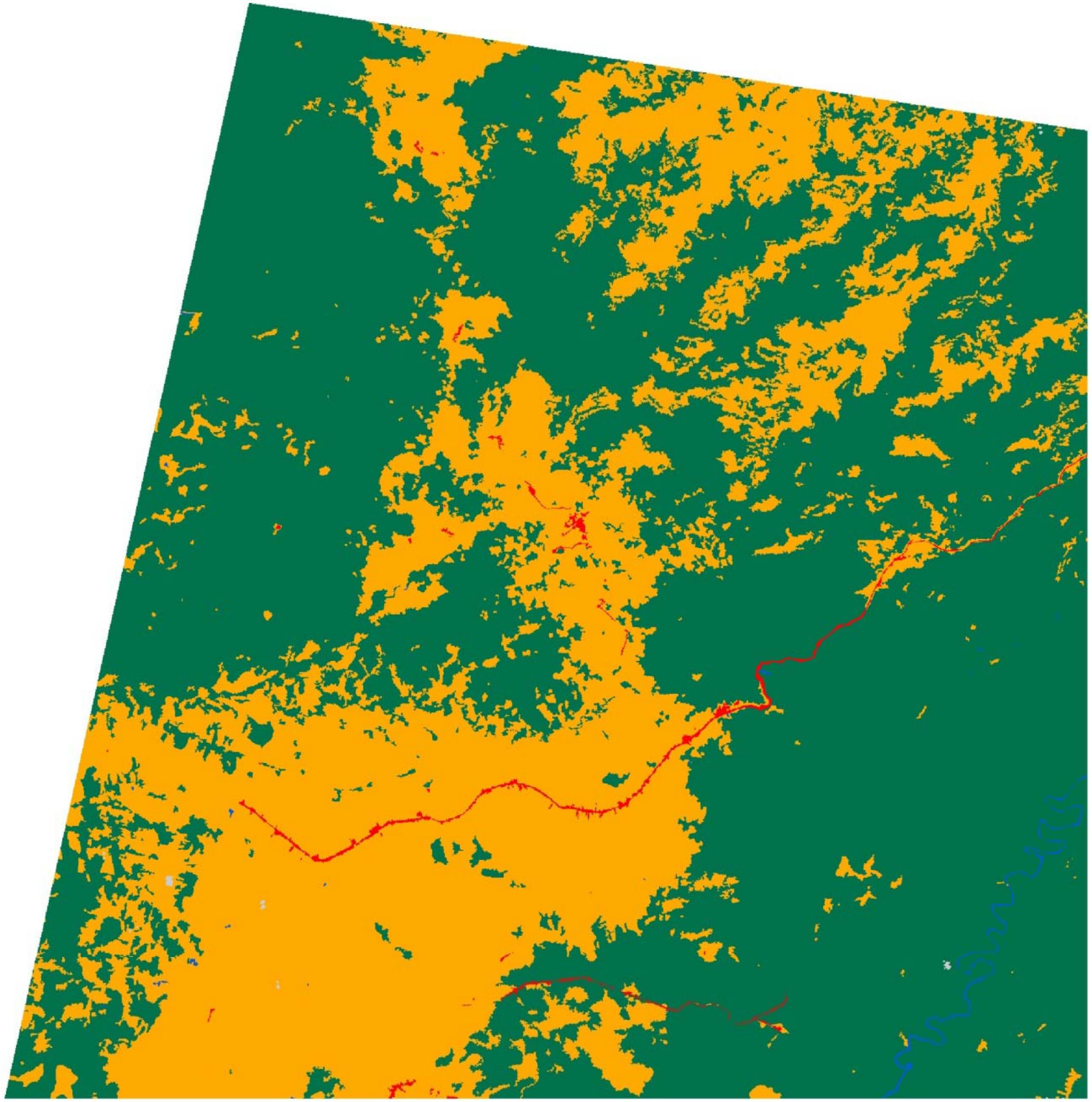


Land use / land cover classification in Mondolkiri province, in 1998

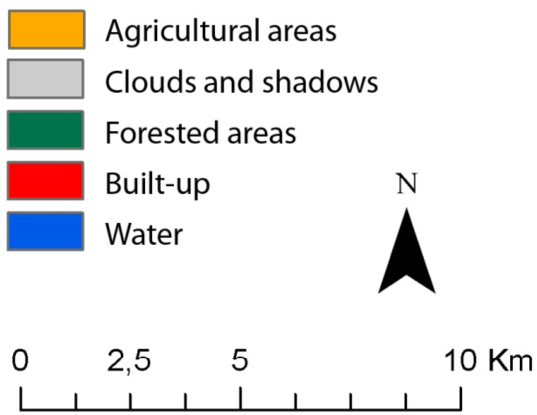


# Results:

## *Land use / cover changes*



Land use / land cover classification in Mondolkiri province, in 2008

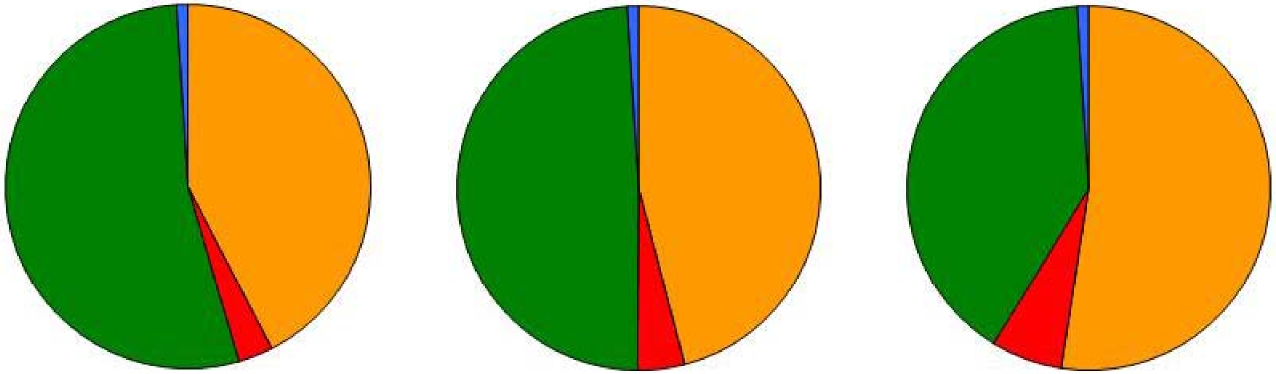


# Results:

## *Land use / cover changes*

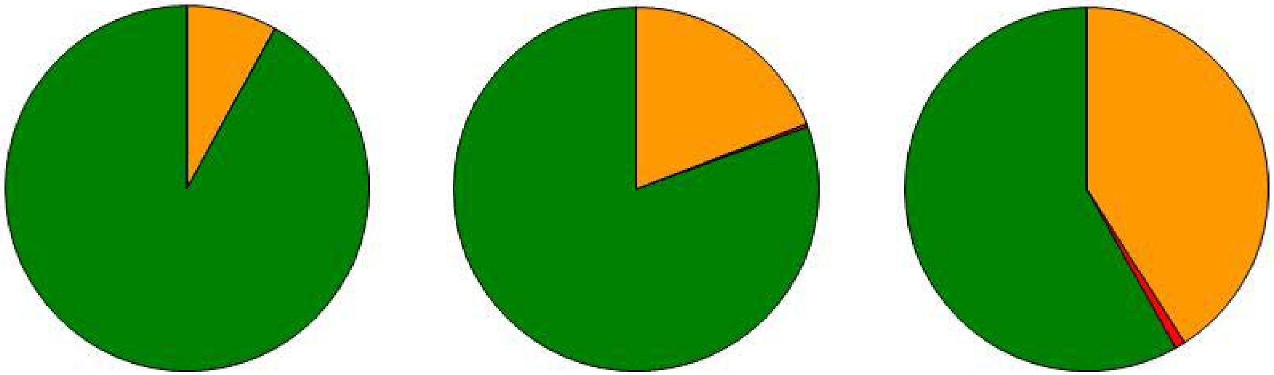
Proportion of each land use / land cover class

### Loei province



1987 1996 2007

### Mondolkiri province



1988 1998 2008

Agricultural areas
Clouds and shadows
Forested areas
Built-up
Water

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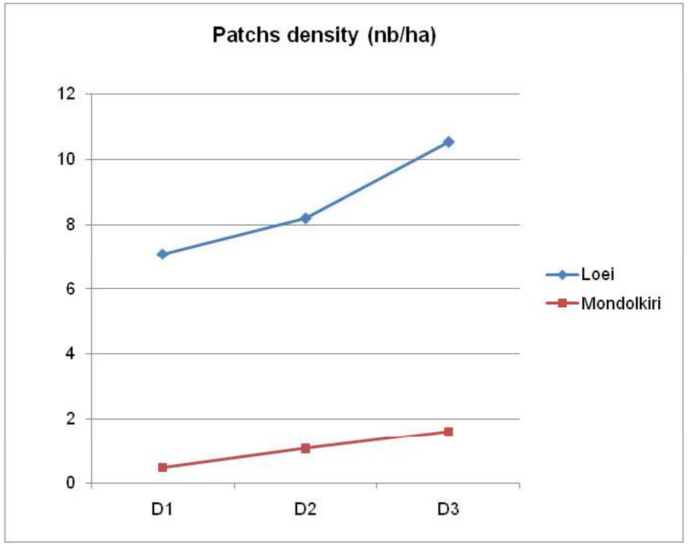
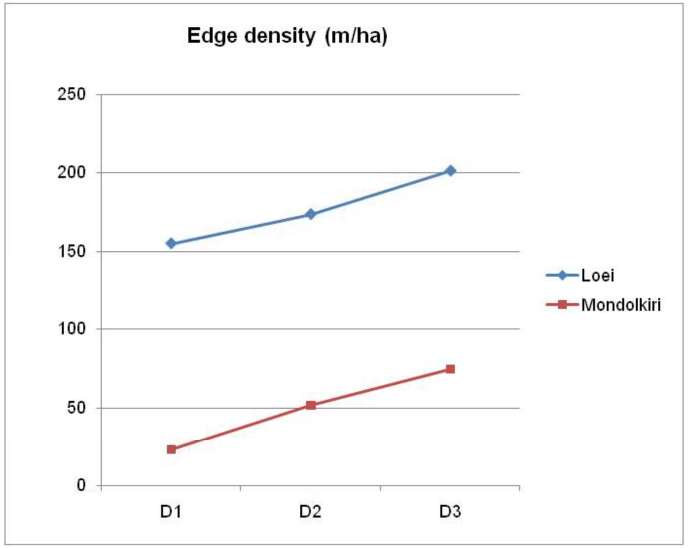
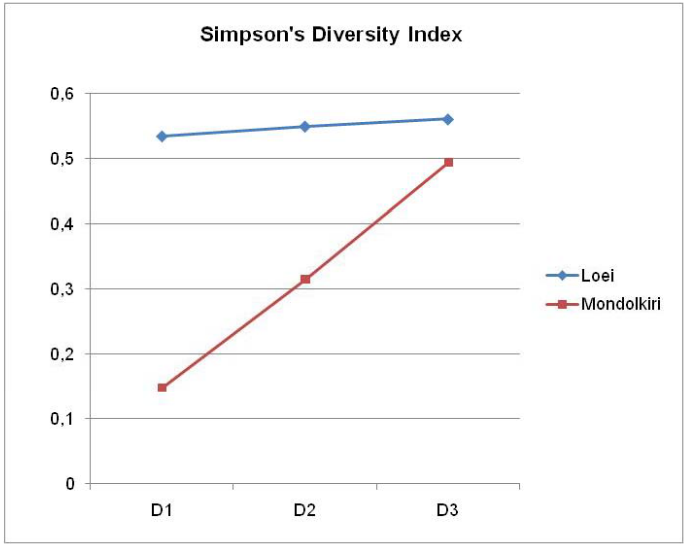
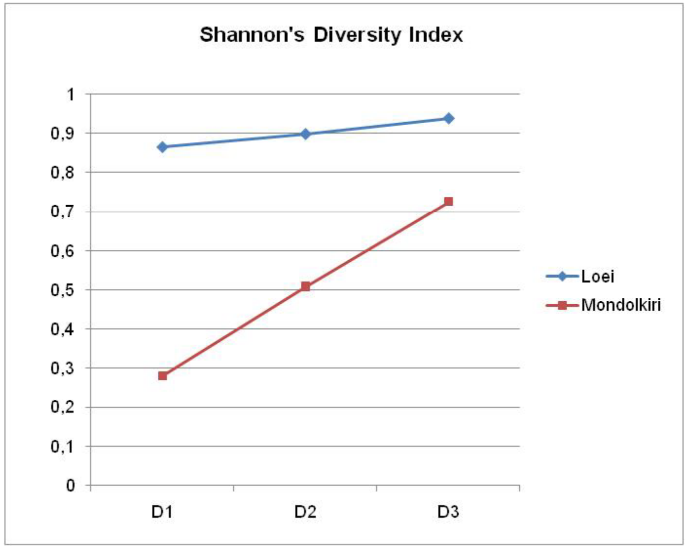
# Results:

## *Land use / cover changes*



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# Results:

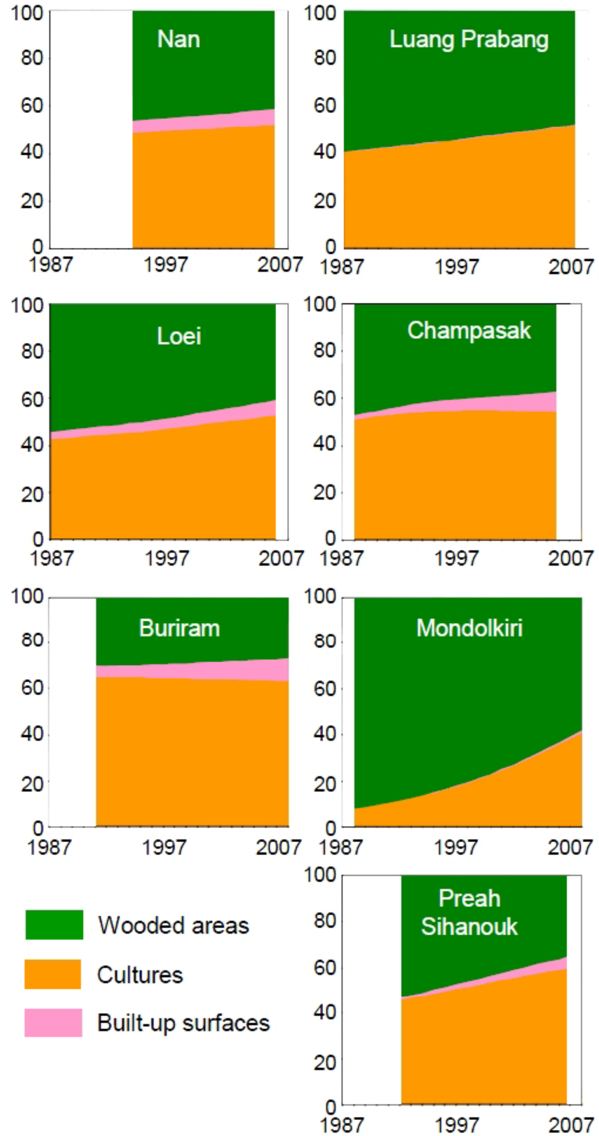
## *Land use / cover changes*

### Diminution of forested areas

- All sites

- Estimation of annual deforestation rates: from 0.65% (Buriram, Thailand) to 1.84% (Mondolkiri, Cambodia)

- Major cause: conversion of forest to agricultural land



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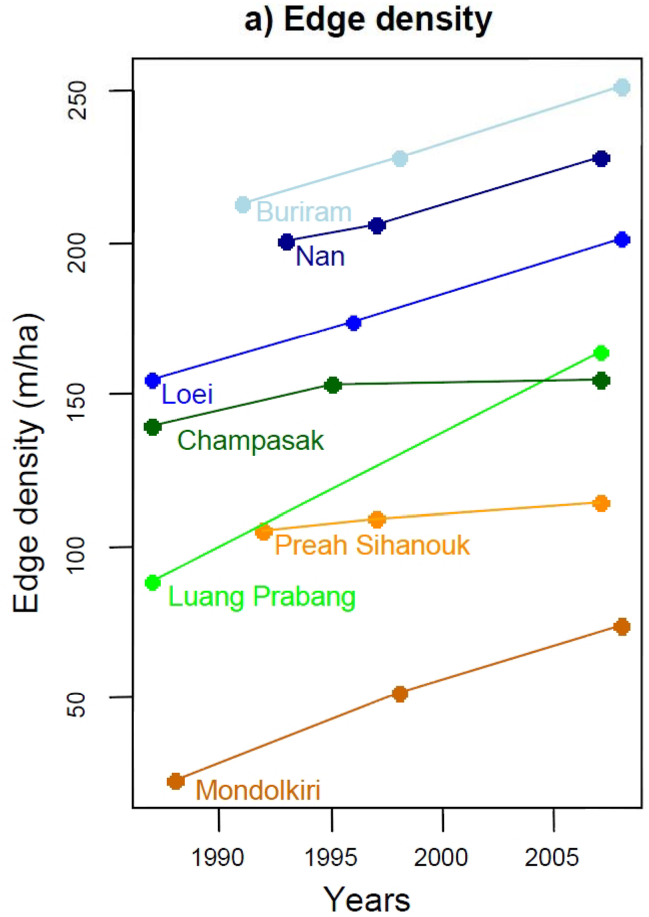
# Results:

## *Land use / cover changes*

### Increase of all landscape indices

- All sites
- Increase of habitat fragmentation and landscape heterogeneity
- Different dynamics between the three countries
  - Fragmentation higher in Thailand and lower in Cambodia



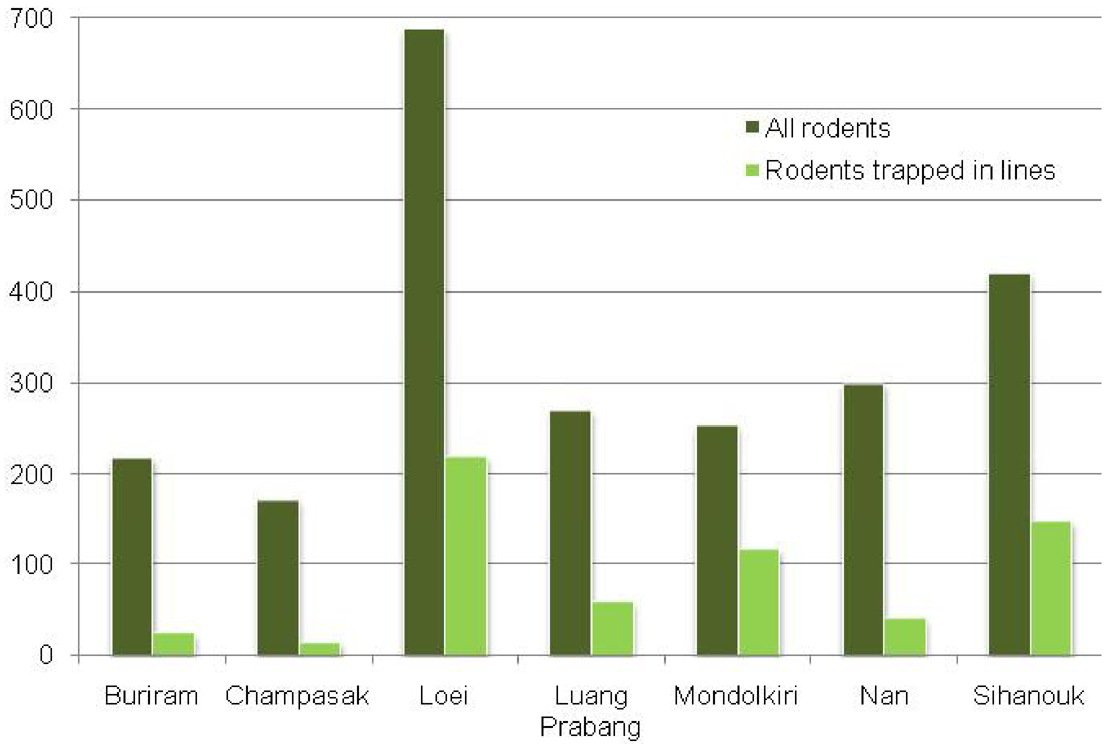

In blue: Thai study sites
In green: Lao study sites
In maroon: Cambodian study sites

# Results:

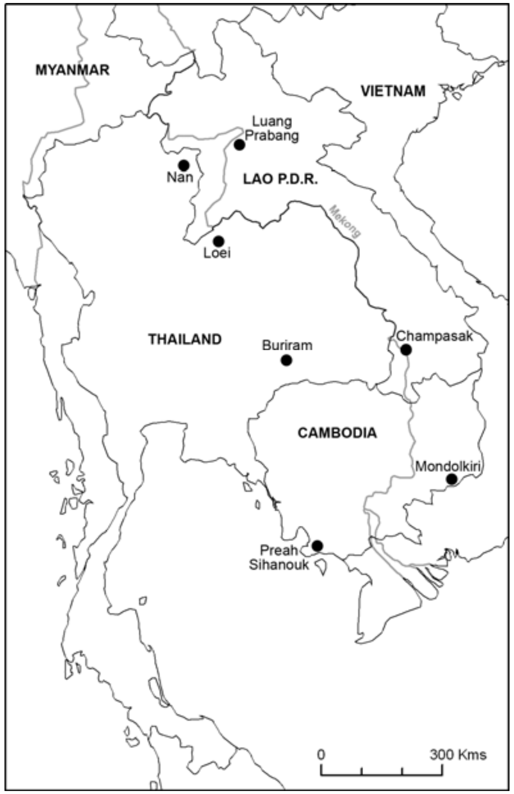
## *Rodent sampling*

• Total of 2,136 murine rodents

• 27 different species (incl. 10 species with less than 10 individuals)




*Trapping success per site*



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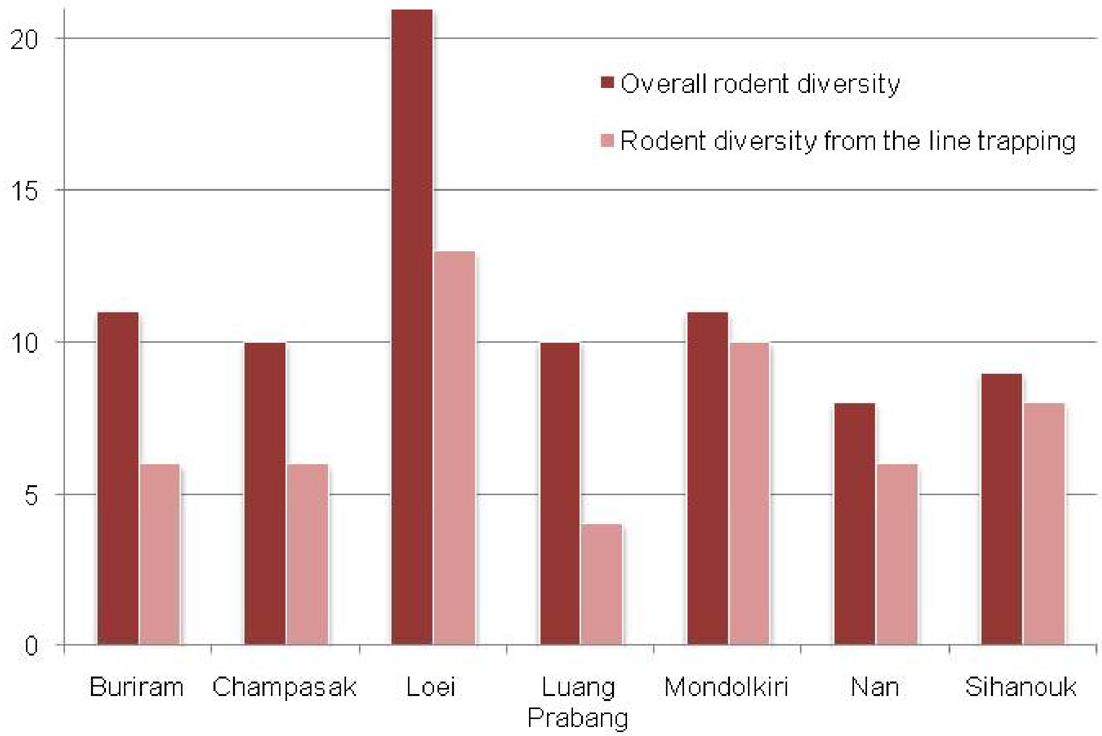


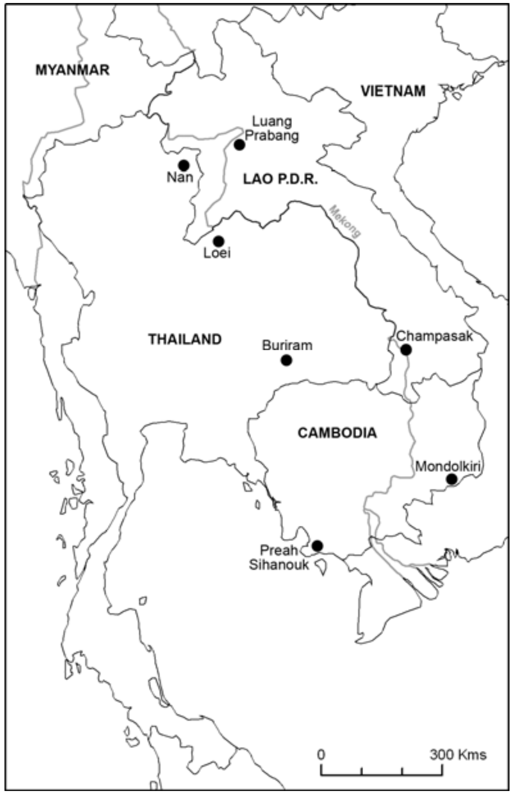


*Species richness per site*

# Results:

## *Ecological ranges*



- Based on global data (DEM, climate):

Example: Range of elevation per species

| Species | Number | Average elevation | Minimum elevation | Maximum elevation | Range |
|---|---|---|---|---|---|
| *Bandicota indica* | 97 | 254,7 | 113 | 558 | 445 |
| *Bandicota savilei* | 49 | 171,1 | 115 | 379 | 264 |
| *Berylmys berdmorei* | 27 | 221,8 | 8 | 358 | 350 |
| *Berylmys bowersi* | 15 | 391,9 | 253 | 587 | 334 |
| *Maxomys surifer* | 86 | 133,0 | 11 | 379 | 368 |
| *Mus caroli* | 91 | 298,5 | 163 | 594 | 431 |
| *Mus cervicolor* | 126 | 220,4 | 154 | 358 | 204 |
| *Mus cookii* | 125 | 402,3 | 206 | 878 | 672 |
| *Niviventer fulvescens* | 63 | 276,6 | 20 | 379 | 359 |
| *Rattus argentiventer* | 37 | 30,8 | 2 | 190 | 188 |
| *Rattus exulans* | 494 | 159,8 | 2 | 379 | 377 |
| *Rattus losea* | 85 | 288,6 | 162 | 379 | 217 |
| *Rattus phylogenetic R3* | 133 | 76,4 | 1 | 316 | 315 |
| *Rattus tanezumi* | 181 | 329,2 | 4 | 587 | 583 |
| *Suncus murinus* | 42 | 5,6 | 2 | 32 | 30 |
| **Total** | **1651** | **217,4** | **1** | **878** | **877** |

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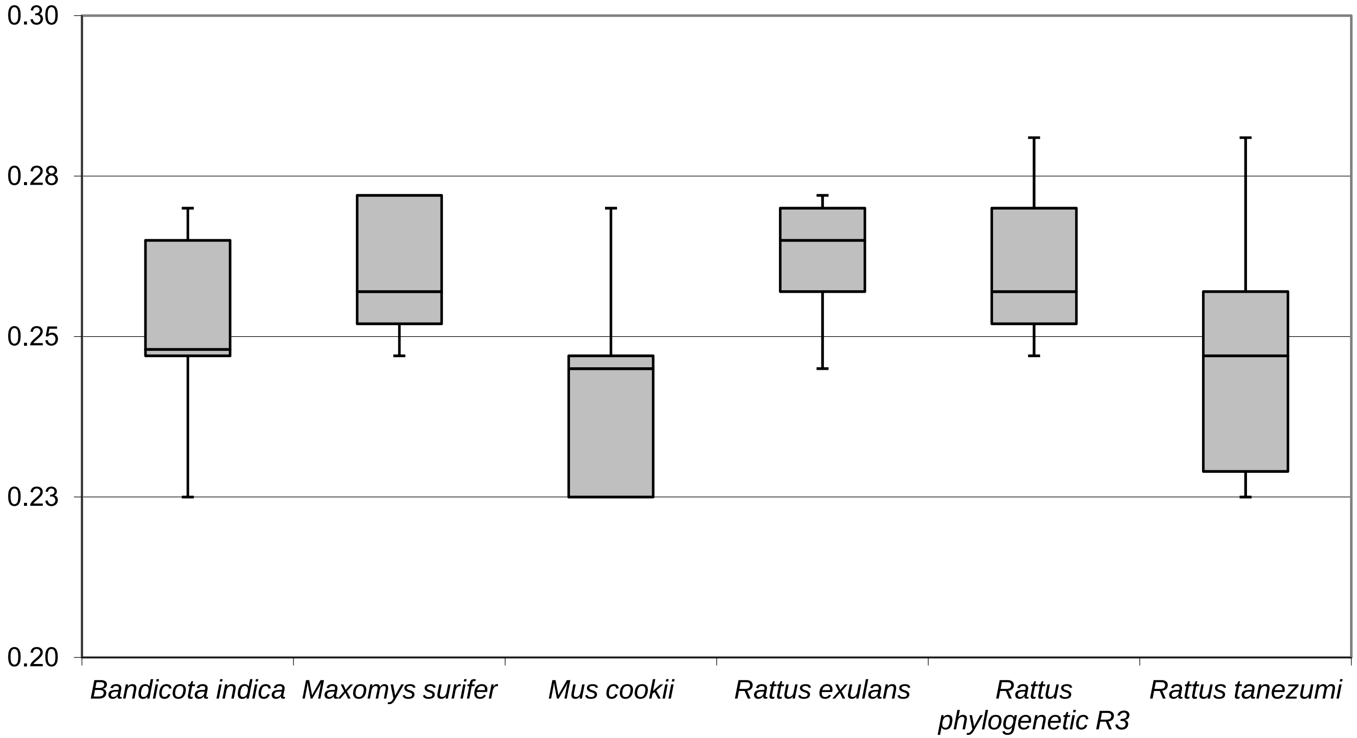
# Results:

## *Ecological ranges*

• Based on global data (DEM, climate):

Example: Range of average temperatures per species




→ Ranges are depending on the study sites

→ Further samplings will enhance the knowledge of each species' ecological ranges.

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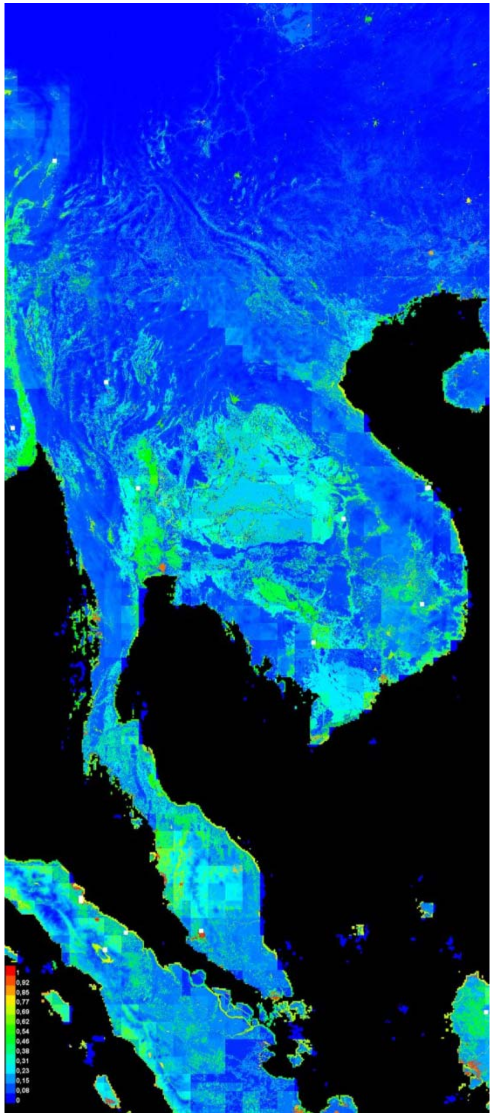
# Results:

## *Habitat Suitability Modelling with Maxent*

- Application of Maxent for HSM:

  Based on global data (landcover, DEM, climate
  Example of *Rattus exulans*

| Variable | Percent contribution |
|---|---|
| Globcover | 67.3 |
| Mean temperature during the coolest month | 24.1 |
| Mean daily precipitation during the warmest month | 4.1 |
| Elevation (SRTM) | 3 |
| Mean temperature during the warmest month | 1.5 |
| Mean daily precipitation during the wettest month | 0 |



Map of potential habitats of *Rattus exulans*

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# Results:

## *Distances to classes*

- Selection of 6 species and samples with an accurate knowledge of the sampling location:

| Site | *Bandicota indica* | *Maxomys surifer* | *Mus cookii* | *Rattus exulans* | *Rattus phylogenetic R3* | *Rattus tanezumi* | Total |
|---|---|---|---|---|---|---|---|
| **Lao PDR - Luang Prabang** | - | - | 37 | - | - | 1 | **38** |
| **Thailand - Nan** | 5 | - | 20 | 1 | - | 9 | **35** |
| **Thailand - Loei** | - | 4 | 22 | 2 | 1 | 2 | **31** |
| **Lao PDR - Champasak** | - | - | - | 17 | 3 | 2 | **22** |
| **Thailand - Buriram** | - | - | 1 | 58 | 22 | 3 | **84** |
| **Cambodia - Mondolkiri** | 1 | 29 | | 38 | 26 | 4 | **98** |
| **Cambodia - Preah Sihanouk** | - | 37 | - | 59 | 53 | 1 | **150** |
| **Total** | **6** | **70** | **80** | **175** | **105** | **22** | **458** |

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# Results:

## *Distances to classes*

- Selection of 6 species:

*Bandicota indica*

*Maxomys surifer*

*Mus cookii*

*Rattus exulans*

*Rattus R3*

*Rattus tanezumi*

**Photos: Herbreteau V.**

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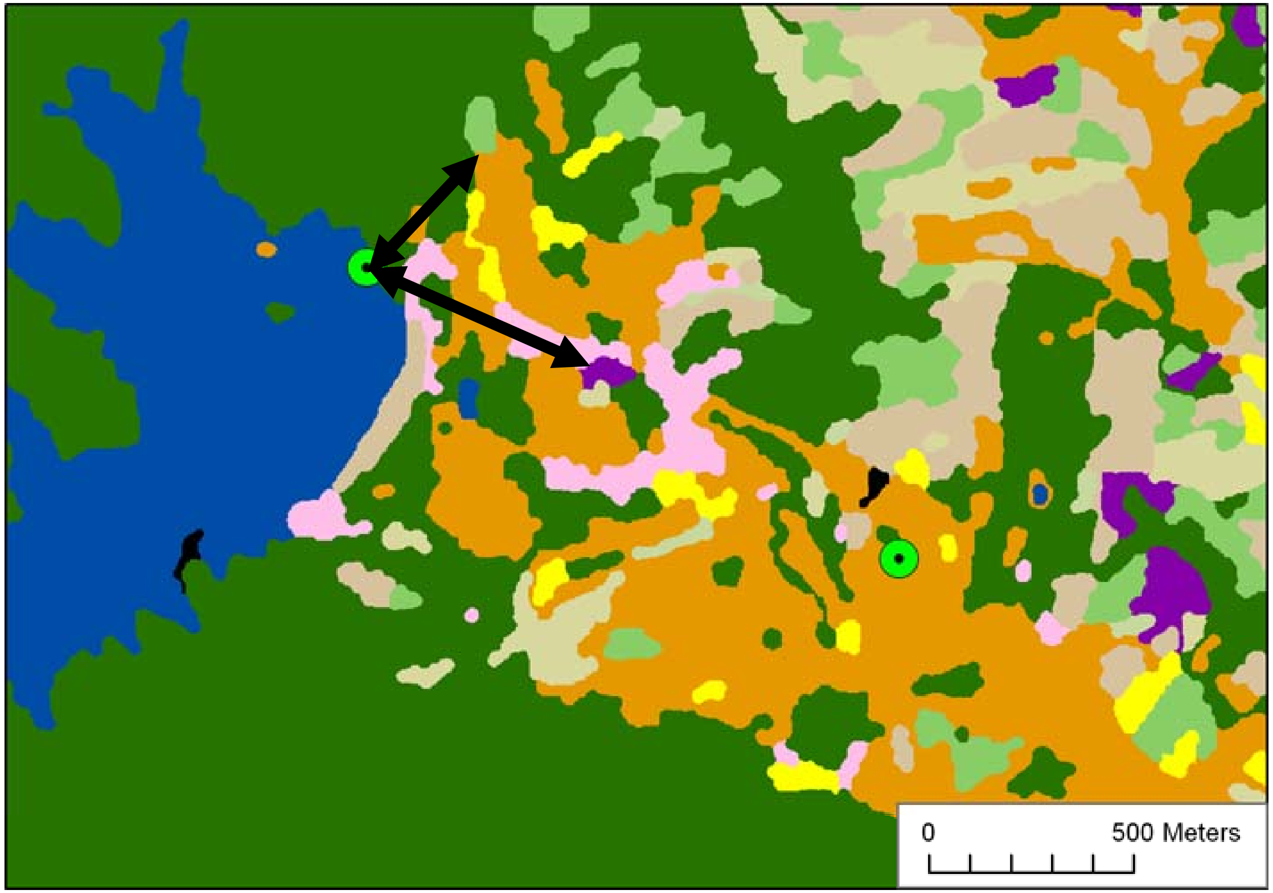
# Results:

## *Distances to classes*

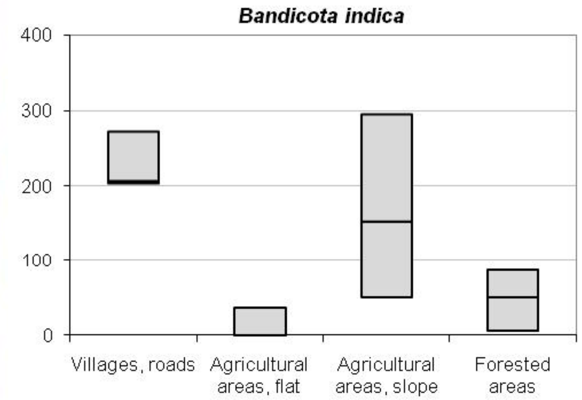
• Shortest distance to each class:

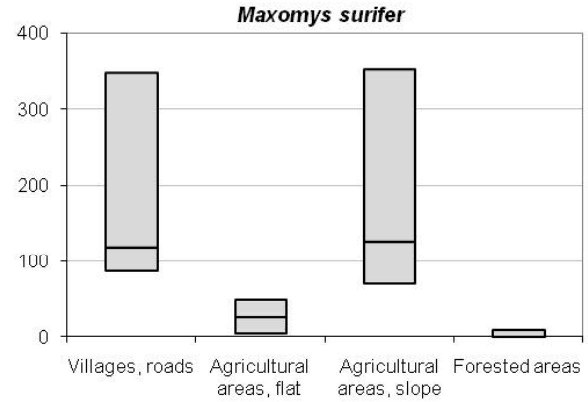


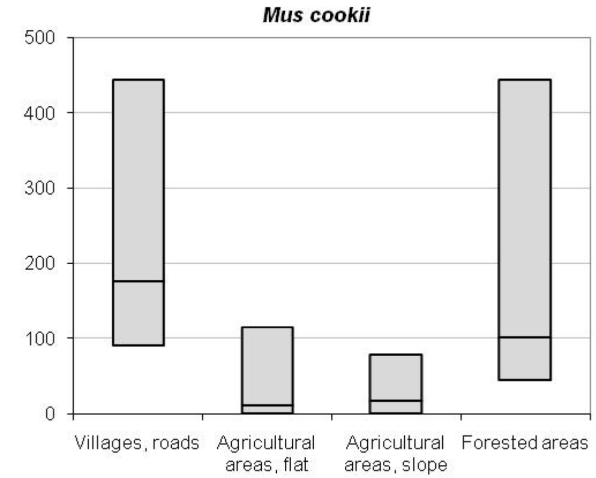
# Results:

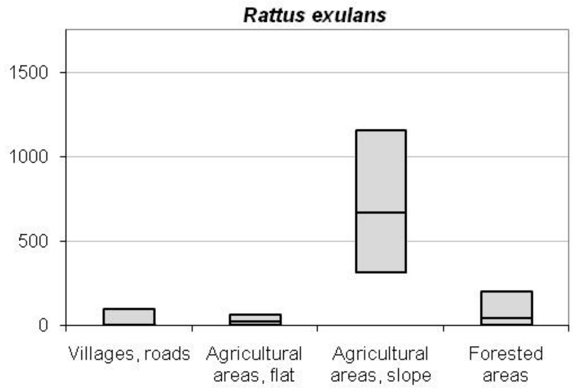
## *Distances to classes*

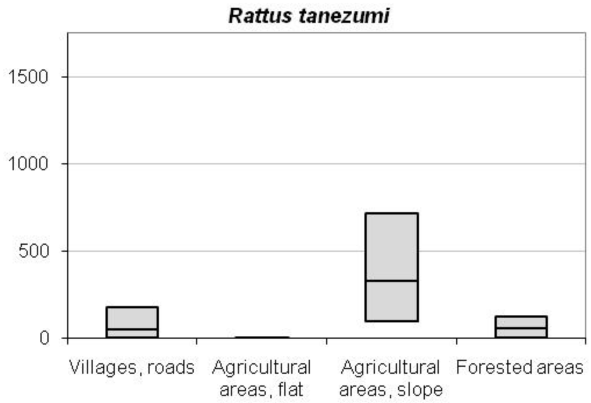
- Shortest distance to each class:

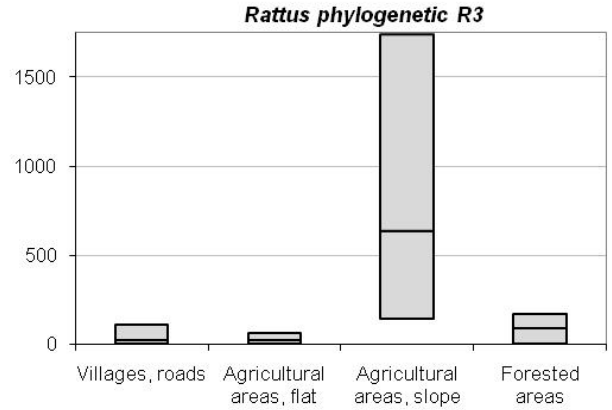


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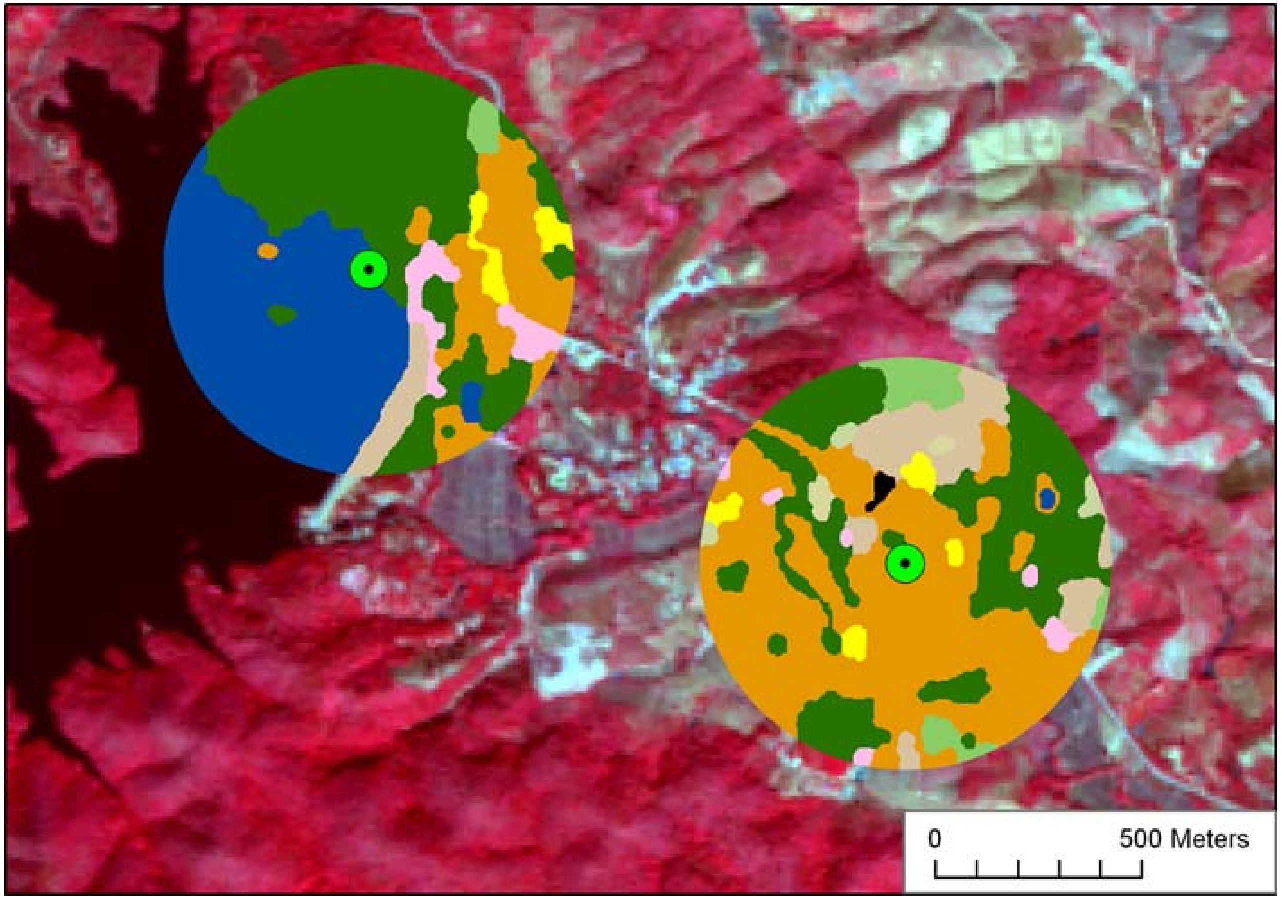
# Results:

## *Landscape metrics*

- Buffer analysis




→ Calculation of the proportion of each class around sampling locations

→ Calculation of landscape metrics: PD, ED, SHDI, SHEI, SIDI.

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# Results:

## *Species prediction*

- Discriminant analysis (forward stepwise):
  - 19 available variables:

    - Longitude, latitude,

    - Elevation,

    - Proportion of 5 classes inside the buffer: Water, Agricultural area-flat, Agricultural area-steep, Roads-villages, Forested areas,

    - Landscape metrics: PD, ED, SHDI, SHEI, SIDI,

    - 6 climatic variables: Rainfall of the driest month, of the wettest month, Annual rainfall, Minimum temperature of the coldest month, Maximum temperature of the warmest month, Average temperature.

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# Results:

## *Species prediction*

- Discriminant analysis (forward stepwise):
  - 19 available variables.
  - The best model can predict 74,5% of the 5 species:

| | Wilks' - Lambda | Partial - Lambda | p-level |
|---|---|---|---|
| Latitude | 0,165954 | 0,702933 | 0,000000 |
| Elevation | 0,138322 | 0,843352 | 0,000000 |
| Annual rainfall | 0,137007 | 0,851449 | 0,000000 |
| Prop. Forested areas | 0,129674 | 0,899598 | 0,000010 |
| Rainfall wettest month | 0,132332 | 0,881530 | 0,000001 |
| Average temp. | 0,123372 | 0,945547 | 0,004464 |
| Shannon Div. Index | 0,125543 | 0,929200 | 0,000541 |
| Edge density | 0,122778 | 0,950122 | 0,007912 |
| Prop. Artificial areas | 0,120147 | 0,970927 | 0,092838 |

# Results:

## *Species prediction*

- Discriminant analysis (forward stepwise):
    - 19 available variables.
    - The best model can predict 74,5% of the 5 species:

| **Species** | % of correct prediction |
|---|---|
| *Bandicota indica* | 63.6 |
| *Maxomys surifer* | 71.8 |
| *Mus cookii* | 89.2 |
| *Rattus R3* | 79.6 |
| *Rattus tanezumi* | 13.0 |
| **Total** | **74.1** |

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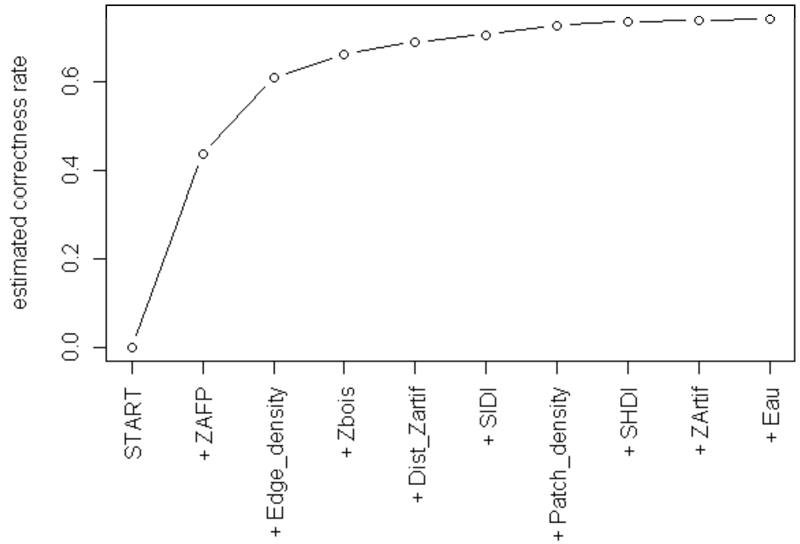
# Results:

## *Species prediction*

- Discriminant analysis (forward stepwise):
  - using only landscape metrics and distances to classes
  - 6 species can be predicted:

| **Species** | % of correct prediction |
|---|---|
| *Bandicota indica* | 94.5 |
| *Mus cookii* | 88.7 |
| *Maxomys surifer* | 78.1 |
| *Rattus argentiventer* | 76.5 |
| *Mus cervicolor* | 51.6 |
| *Rattus losea* | 43.5 |
| **Total** | **75.9** |



# Discussion:

## How to extrapolate local results?

• High resolution data (i.e. land cover classification) not available over the distribution of the species.

→ Possibility to calculate similar landscape metrics with GlobCover

GlobCover

| | | |
|---|---|---|
| 2 | 2 | 5 |
| 4 | 3 | 3 |
| 4 | 3 | 3 |

Reclassification

| | | |
|---|---|---|
| 10 | 10 | 10000 |
| 1000 | 100 | 100 |
| 1000 | 100 | 100 |

Focal statistics (sum)

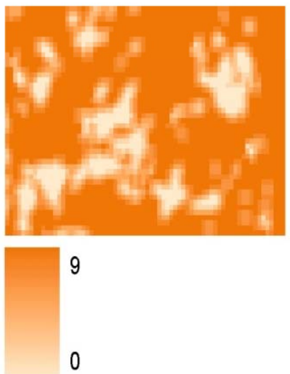
| | | |
|---|---|---|
| . | 00011220 | . |
| . | 00012420 | . |
| . | 00002400 | . |

3rd class…

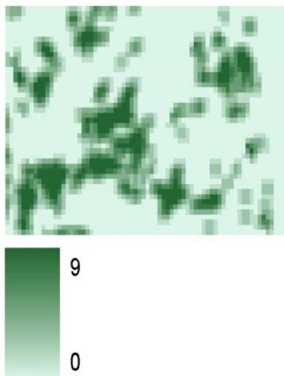
Extraction for each class

| | | |
|---|---|---|
| .. | 2 | .. |
| .. | 4 | .. |
| .. | 4 | .. |

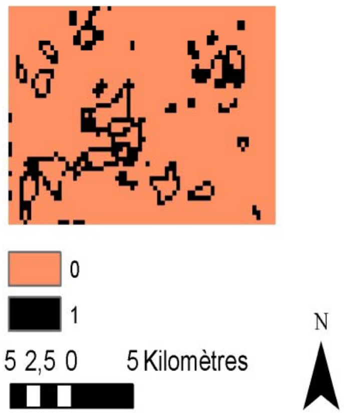
Number of pixels classified as agriculture in a 3*3 window



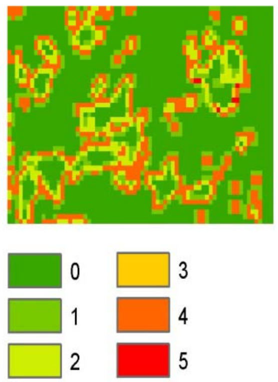

Number of pixels classified as forests in a 3*3 window




Calculation for *Maxomys surifer*:
2 < nb pixels forests < 6
2 < nb pixels agriculture < 5
Built up = 0




Sum of calculations for each species



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## Discussion:

### Limitations of the use of high resolution data

- A limited approach in time:
    - Animal samples / land cover are described at a given date
    - Environmental changes can be very fast:

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# Discussion:

## Limitations of the use of high resolution data

• A limited approach in time:

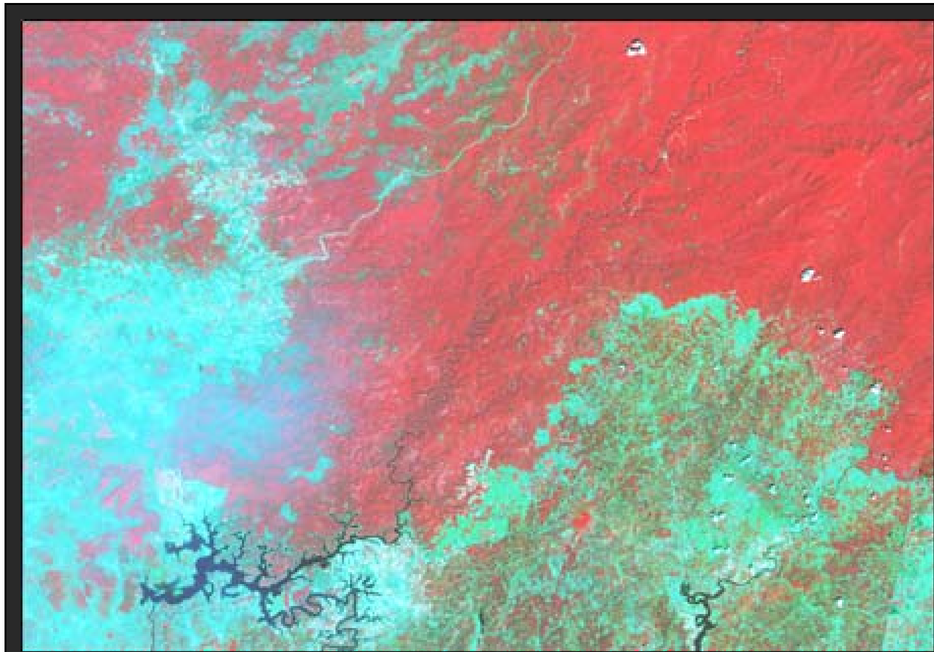
- Animal samples / land cover  are described at a given date

- Environmental changes can be very fast:

→ Need to process images regularly.

→ Higher temporal resolution of remote sensing data is required for a proper land-cover changes monitoring.

→ Potential of medium resolution satellite images (Landsat), and automated classifications (as a future perspective).




Source: Herbreteau V., 2010, Mondolkiri-Cambodia fromSpot I HRV and Spot V HRG images)

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## Discussion:

## Limitations of the use of high resolution data

- A limited approach in time:
  - Animal samples / land cover are described at a given date
  - Environmental changes can be very fast:

- Difficulties to integrate the human activities impacting land use and rodents dynamics:

  Agricultural shifts, hunting, introduction of species, etc.

## Perspectives:

- Socio-economic investigation on land uses to identify underlying driving factors.
- Study of the impact of environmental changes on biodiversity of rodent and pathogens communities.


# Acknowledgements

CERoPath project (Dir. Serge Morand)

Colleagues: Stéphane Dupuy, Tristan Feyfant and Annelise Tran

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